Topics in Sustainable Energy: An Economic Analysis of Net Demand Volatility Management

Adam David Hutchinson

PhD in Economics

Department of Economics

University of Warwick

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Summary

A low carbon future poses the question, how will low carbon technology be integrated? One possibility is to retain back-up conventional generators. Other possibilities are technical energy storage, and for demand side management to play a more important role. With the advent of smart metering it is possible consumers could be given real-time prices from their energy supplier.

If energy storage is to be implemented investors and stakeholders must have an idea of the likely revenues. Chapter 1 estimates arbitrage revenues for a small price taking store in a GB 2050 electricity market scenario. We do so be estimating equilibrium market prices, which provide us with a market based approach to valuation. It also estimates the effect that the characteristics of the store, and market concentration has on revenues.

If energy storage is to be installed in enough capacity to smooth out large fluctuations in net demand then the economics of a small, price taking, store are no longer valid. An energy store would become a strategic player in the market and a Nash equilibrium between generators and the store must be reached. Chapter 2 proposes a methodology for estimating large scale energy storage strategies and revenues, and estimates them.

Chapter 3 then turns to address time-of-use (TOU) tariffs. One potential threat to TOU tariffs is the fear they will lead to winners and losers and that they may be regressive or affect certain sectors of society more than others. Here we explore these issues by taking advantage of a unique data-set, the Household Electricity Survey (HES). We analyse the distributional effects of various revenue-neutral TOU tariffs which are designed to reflect the true cost of meeting electricity demand. We perform this welfare analysis under both the assumptions of no demand response and demand response respectively.

Part I

Small Scale Energy Storage Arbitrage in a 2050 GB Electricity Market Scenario

1 Introduction

By 2020 the UK is set to provide 15% of its energy needs from renewable sources. This is set to rise to 30% by 2030 and by 2050 CO_2 emissions are set to be reduced by 80% relative to 1990 levels [1]. These renewable technologies including solar, wind, and tide, among others, vary in their potential for power provision, energy payback, and economic viability. However, a common feature of these technologies is their non-dispatchable nature. This inherently leads to increased volatility and uncertainty in energy supply, imposing real costs for distribution and generation. This increased volatility potentially provides opportunities for arbitragers to buy in times of excess supply and sell when generation is scarce. Furthermore, the aims of private arbitragers and a benevolent system planner should coincide. At times of highest demand, and so highest cost, an arbitrager will want to sell, replacing the highest marginal cost producers. At times of low demand, and so lowest cost, an arbitrager will want to buy, potentially avoiding costly shutting down of generators as well as reducing the average cost of generation.Whilst there are several potential sources of revenue for an energy storage firm, including the short term operating reserve (STOR) market,

[1] DECC [2011].

capacity market, and a range of ancillary services if the storage technology permitted, we provide estimates of the likely returns to arbitrage. This provides an idea of how low energy storage costs may have to become, or how large earnings from other sources have to be in order for energy storage technologies to become commercially viable. We therefore aim to estimate the potential arbitrage returns to a small scale energy store for varying specifications of the store in a future electricity market scenario. Given this optimisation we are able to estimate how much each of the characteristics of the store: round-trip efficiency, flow constraint, and storage level constraint affect the revenue and capacity factor of the store. We estimate elasticities between arbitrage revenue and storage characteristic, which is unique to this study. We also explore how arbitrage revenues are affected by concentration in the wholesale electricity market. This is something unique to this study and provides an idea of what kinds of electricity market reform may be good or bad for arbitrage revenues.

We go beyond previous studies by explicitly modeling the market the storage firm would be operating in. This allows us to estimate a time series of market clearing prices in a 2050 GB electricity market scenario, for the energy storage firm to maximise over. Importantly this provides us with market founded spreads of electricity prices. This allows our estimates of energy storage's value as an arbitrager to be more market based than previous studies.

In order for us to estimate the likely returns to energy storage we must have a price profile over which it can maximise. However, large scale renewable generation is not yet a reality and net demand is not as volatile as it may become. Therefore, using current prices could be misleading. To combat this we compute a supply function equilibrium (SFE) for a 2050 Great Britain (GB) electricity market scenario. Supply function equilibrium was chosen rather than other forms of competition, such as Cournot, since it has been shown in Willems, Rumiantseva, and Weigt (2009) to approximate electricity market prices better than competing models. Cournot, for example, tends to overestimate the markup. We apply the supply function equilibrium to 2050 GB stylised electricity demand which provides us with prices over which the store can maximise. Valuations of the store's worth and its potential for smoothing are then calculated from these optimisation results. Section 2 introduces SFE in greater detail, and section 4 explains the empirical strategy.

Firstly, a note on what we mean by energy storage. Traditionally energy storage has been provided by pumped hydroelectric energy storage such as Dinorwig in the UK, and Bath County Pumped Storage Station in the US. However, the installation of pumped hydro is limited by the availability of suitable locations. There are, however, many other potential energy storage technologies such as compressed air energy storage (CAES), seasonal thermal stores, hydrogen, and batteries, among others. Here we do not specify a specific technology but instead treat storage as a 'black box' for which we can set the parameters. Certain mixes of these parameters will describe certain storage technologies. We can also consider these results as a slightly different form of energy storage - demand side management. Just like technical energy storage there are constraints on how much can be curtailed (stored) each hour, and constraints on just how much can be postponed in total at any one point in time. Although not a constructive demonstration of demand side management where consumers would equate the marginal rate of substitution between energy use and curtailment, and the price of doing so, it does perhaps capture one aspect well. That is the idea that whatever is curtailed now must be executed later, and perhaps to a greater extent than it would have been before. For example domestic heating could be postponed and room temperature kept within designated limits. However, when it is eventually heated it may take more energy to return it to a desired temperature than if a constant temperature had been sustained throughout. In effect heating or some other use of electricity could take the form of a convex function. This is captured here by input and output efficiency.

Why might energy storage be beneficial in a low carbon future? There are times when renewable energy production falls substantially and potentially for sustained periods requiring either some sort of net demand management or spare generation capacity (see figure 20 for a time series of renewable output scaled up from 2009-10 to 2050 levels). Curtailment of renewable energy also occurs occasionally due to the ramping constraints of conventional generators. This is where conventional generators are prepared to pay or accept very low prices in order to keep on producing so as to avoid costly ramping. This could be avoided with storage. One alternative to storage or demand management is the use of inter-connectors. Creating a larger, more integrated grid is of benefit for a variety of reasons, as are explained in Archer & Jacobson (2007)., however weather systems can stretch across large areas of Europe. There is therefore only limited scope for diversifying renewable generation risk across countries (Andrews, 2015). However, there is the potential to diversify risk between countries with a large penetration of renewables and those with extensive hydroelectric and pumped storage capacity. Green and Vasilakos (2012), for example, analyse electricity trade between Denmark and other Nordic countries, and find that by internationally trading electricity they are able to optimally deal with intermittency in wind generation. There are however constraints on the capacity of inter-connectors and they size of fluctuations they can manage. Storage therefore may be able to offer improved security of supply given the shortcomings of other methods of risk minimisation.

Electricity storage is able to offer shorter term solutions such as balancing and frequency services. These are potentially lucrative and have been evaluated in the literature, for example by Black & Strbac (2006) & (2007), Pelacchi & Poli (2010), and Paatero & Lund (2006) & (2007). The remit of this paper is different however, in that it is addressing the viability of energy storage as an arbitrager.

Some previous studies have analysed the overall system value of arbitraging energy storage in Great Britain by looking into how energy storage could be used to minimise the cost of generation. This is done by storing when the marginal cost of energy production is low, and releasing when the marginal price is higher, for example when the marginal plant is very high marginal cost and the starting up cost of the plant may also have to be recovered in the wholesale market. This leads to potentially very high marginal costs of production. Grünewald et al. (2011) analyses the role of an arbitraging large scale energy store in a GB low carbon future.

The Energy Research Partnership (2011) similarly explores energy arbitrage in the UK. However, their focus is primarily on energy storage's ability to provide a reliable energy supply in the face of large penetration of renewables, but in particular in pathways to achieving the UK's emissions goals. They find that energy storage can help to manage the large-scale deployment of renewable generation, and also the electrification of space heating[2]. They also find storage has the potential to substitute for new peaking generation plant, and also help the transmission system handle increasing power flows. However, they do find that energy storage technologies are unlikely to be deployed on a large scale under current market and regulatory conditions. They recommend that both storage technology cost reductions, and a market and regulatory framework which recognises the benefits energy storage brings (such as security of supply, ancillary services, and system inertia). However, they do point out that since energy storage is an enabling technology its potential role will be defined by

[2]Currently space heating is primarily met by gas in the UK.

developments across the energy system.

In this analysis we go further by estimating equilibrium market prices, in a defined future energy scenario, for the storage firm to maximise over rather than storage taking up spare renewable output. Previous literature has also assessed the potential returns to energy storage from the investors viewpoint. Particularly from arbitrage in the US. For example, Drury, Denholm, and Sioshansi (2011) value the possibility of energy storage providing operational reserves, and arbitraging in several US markets. Sioshansi et al. (2009) also estimates the arbitraging profit of an energy store, however in Pennsylvania-New Jersey-Maryland (PJM).

Byrne and Silva-Monroy (2012) analyse the potential profit of energy storage with combined services provision in California Independent System Operator (CAISO). However, they do so by using historic market prices with perfect information. However, as Teng (2015) notes, in a future system with high renewable generation penetration, electricity prices would become more volatile, as well as uncertain. Here we attempt to tackle the first of these critiques.

There has also been considerable research into the value of co-location, and co-ownership of storage and intermittent electricity sources for example Sioshansi (2011), Madaeni, Denholm, and Sioshansi (2011) who look at the added value of storage in connecting transmission connected renewable generation in places with high load factors to demand centres. Research has also aimed to asses how well storage can be used to improve the value of intermittent renewable generation, for example Solomon et al. [2010], and Wilson et al [2010]. Gill et al. (2013) have also explored how energy storage can be used to increase the revenue of non-firm wind generation. While we concentrate here on arbitrage it is possible that stores would diversify their revenue streams to incorporate balancing and frequency services along with arbitrage, and the capacity market.

Strbac et al. (2012) explore multiple-service provision from energy storage. They take a whole-systems approach to estimating the value of storage, and as such tend to find values higher than those suggested by previous research. These include savings in generation capacity, interconnection, transmission, and distribution networks as well as savings in operating costs. They find that the relative share of each of these savings changes greatly over time, and is different across assumptions taken. Generally the value of storage is greatest in scenarios with high renewable generation shares. This is a result of storage being able to be used to reduce the amount of renewables curtailment. They also find that storage is at its most valuable when peak shaving, and so storage duration greater than 6 hours become of little value. They also find that distributed energy storage is of significant value in reducing distribution network reinforcement expenditure. However, they do note that the demands placed on storage to achieve each of these goals varies greatly, and it would be likely that several storage technologies would be needed to achieve the full suite of benefits of storage.

stoRE (2013) and Tuohy and O'Malley (2011) also investigate multiple-service provision from energy storage. stoRE (2013) analysed how energy storage could be used to facilitate high penetration of renewable generation in Germany. However, Tuohy and O'Malley (2011) use stochastic scheduling to calculate the optimal split of energy storage capacity between activities. They do so for arbitrage and ancillary service provision under a variety of system conditions. This is particularly useful under high renewable penetration since generation is inherently stochastic.

In addition, the 'Smarter Networks Storage' project (2016) provides evidence of the capability of grid scale battery storage and its ability to serve multiple revenue-earning streams. The trials, which commenced in 2014, offers evidence of how grid scale battery storage can be deployed within the GB electricity system. While they find frequency response the best the most profitable application currently, one issue it addresses is their ability to to accomplish different objectives at the same time. They demonstrate that many activities can overlap, for example, local distribution congestion management, triad avoidance, and national peak shaving. As such they conclude that contracts for storage services should allow deployment for multiple applications to support business cases.

While most of the literature we have discussed relates to system-wide and transmission level usages of storage, the literature has also assessed how energy storage can be used at distribution level. Pudjianto et al. (2014) shows the benefits of energy storage in supporting the distribution network. That is in managing constraints on the distribution network.

Teng et al. (2015) also analyse the advantages of energy storage in the distribution network, however this time in analysing the value it might deliver to investors. They do this for a range of objectives: energy and ancillary service markets, revenue maximisation in the context of feed-in tariffs, and by facilitating reductions in carbon dioxide emissions. They find the key drivers for the value of energy storage in this context are the parameters of the store itself, network constraints, prices of energy and ancillary services, and the characteristics of the energy system in which they are integrated.

2 The Model

Supply function equilibria (SFE) was first introduced by Klemperer and Meyer (1989), and applied to the GB electricity market by Green and Newbery (1992). Generators are assumed to compete in supply functions, that is a schedule of quantities and prices offered to the market. This allows firms to be more flexible than either choosing quantity (as in Cournot competition) or price (as in Bertrand competition). In Klemperer and Meyer (1989) a supply function is argued on the grounds of uncertainty in the demand function. Green and Newbery (1992) showed this as equivalent as variation in the demand function from changing demand conditions at different times of the day and week. Willems, Rumiantseva, and Weigt, (2009) show that SFE provides a better approximation electricity markets in the long run than competing models of competition such Cournot, and so we use SFE in order to estimate a supply function for the GB electricity market.

In SFE, firms maximise profit subject to beliefs about the residual demand function, which is assumed to be a linear function of price. The residual demand function being gross consumer demand, net of other generators scheduled quantity. An SFE therefore constitutes a Nash equilibrium between the large generators in the market and is the sum of best responses for different realisations of the demand function. Firms maximise their own profit function:

$$\pi(p,t) = p\left(D(p,t) - \sum_{j\neq i} q_j(p)\right) - C_i\left(D(p,t) - \sum_{j\neq i} q_j(p)\right) \tag{1}$$

where p denotes the market price at each point in time, and $D(p,t) - \sum_{j\neq i} q_j(p)$ is the residual demand faced by the ith firm at time t. Finally, $C_i(q)$ is the total cost for firm i of producing q units of electricity. The first order condition leads directly to the supply function:

$$q_i(p) = \Big(p - C_i^{'}\left(q_i\left(p\right)\right)\Big)\left(-\frac{\delta D}{\delta p} + \sum_{j \neq i} \frac{\delta q_j}{\delta p}\right) \tag{2}$$

This can be simplified by taking the symmetric case where all generators are the same size with the same cost function. Evans and Green (2005) show this is a good approximation for a linear case where exact solutions exist. Like Green and Vasilakos (2010) we assume 6 symmetric firms for our base case and is derived from the inverse of the Herfindahl Index. This implies little change in concentration from current levels, however, we do explore differing levels of concentration in section (5.4).

The industry supply function, once calculated from the first order conditions above, provides us with market price, market supply pairings. The demand data, scaled to 2050 levels, and netted of 2050 renewable electricity production, is then passed through the supply function in order to provide our 2050 time series/schedule of prices. See section (5.1) for more detail.

We then maximise the revenue of a small scale price taking energy storage operator over this price schedule. Optimisation is based upon the method described by Connolly et al. (2011). The optimisation procedure is provided by Edward Barbour[3]. We estimate returns for a variety of charging and discharging efficiencies[4], flow, and storage capacity constraints. There is no technical marginal cost to storage operations, for example a fuel cost. The main determinants of storage operations should be the predicted spread, efficiency losses, and the flow, and capacity constraints. The omission of technical marginal costs should not affect our results greatly since it is equivalent to either a slightly higher buy price, or slightly lower sell price, which is captured by the round-trip efficiency. The storage firm then maximises revenue over the time horizon

[3]See Barbour et al. [2014], and www.energstoragesense.com

[4]Set equal for simplicity.

providing us with a storage and revenue profile. The storage firm is small relative to the market size and so we assume it is a price taker. The storage firm therefore maximises profits given a price series:

$$\max \sum_{t=1}^{T} p_t q_t^s \tag{3}$$

where q_t^s is the quantity the storage firm either buys (-) from or sell (+) to the market at time t.

Subject to:

$$\bar{q}^s > q_t^s > \underline{q}^s \forall t \in T \tag{4}$$

$$\bar{L}^s > L_t^s > 0 \forall t \in T \tag{5}$$

where L_t^s is the level of the store at time t given input/output efficiencies of e^{in} and e^{out} respectively.

It is important to note that in using SFE we are assuming the GB wholesale electricity market is being operated as a pool, or a multi-unit auction and not being operated as a bilateral auction as is the case today.

3 Data

In order to calculate a supply function equilibrium for a 2050 scenario we must have a belief over future demand profiles. We therefore take aggregate electricity demand data, provided by the National Grid[5], for the UK at the half-hourly level between the 1st of January 2011 and the first of January 2013 and scale

[5]See National Grid Data Explorer [2015].

this up to 2050 levels in line with the central predictions of Ault et al. (2008). This equates to 1.1% compound growth per year. However, w do not alter the profile of demand to represent changes in consumption patterns as predicting aggregate consumer demand profiles (both daily and seasonally) is beyond the remit of this paper. Furthermore, an assumption made on the shape of daily or seasonal demand would drive prices and associated storage revenues too much for comfort. Whilst an assumption of unchanged electricity demand profiles is potentially unrealistic, all that is important to an arbitrager is the spread and timing of demand. If these remain roughly the same then our results are still valid.

We do, however, want to take into account potential future net demand volatility generated by the increased penetration of renewables. By 2050 40% of the UK's electricity needs are set to be supplied by renewables (DECC, 2011). We therefore need some belief over half hourly renewable energy production and so we take National Grid metered wind turbine generation [6] for the the same time period. Weather conditions partly drive electricity consumption decisions and so wind turbine output and consumer demand cannot be matched together ad hoc[7].

Wind turbine generation is scaled up to 2050 installed capacity levels by the ratio of 2050 generation capacity to installed capacity at each point in time[8]. Wind turbine generation is then netted from demand. This provides us with the net demand profile to be met by generators[9].

[6]Data on other types of renewable generation were not available for the whole period. Wind turbine generation also currently makes up the majority of UK renewable electricity generation.

[7] Table 9 in the appendix shows summary statistics of both observed demand, and renewable output.

[8]Information on installed wind turbine capacity was obtained from Renewable UK. See http://www.renewableuk.com/.

[9] See figures (18), (19), and (20) in the appendix for a time series of of gross demand, net

It would be interesting to use higher resolution data, where we would be able to explore arbitrage returns for managing short run net demand fluctuations in ancillary markets. However, wind turbine generation is only measured at the half hourly level, furthermore, short run wind turbine output volatility is reduced when there is deeper renewable penetration (IEA, 2005).

In order to estimate the supply function equilibrium we must have a belief on the composition of electricity generation in 2050 and so the marginal cost function for electricity generation. We take DECCs MARKAL 3.26 analogous scenario for 2050[10]. Included in this is the predicted future composition of electricity generation technologies. The corresponding marginal costs are taken from DECC (2012) which include CO_2costs priced at 2050 carbon prices. Figure 1 shows the marginal cost function for the industry as well as the equilibrium supply function. The marginal cost function is step-wise increasing as the industry moves along the merit order from low marginal cost technologies to higher marginal cost ones, from nuclear to coal to gas.

The responsiveness of demand to price i.e. the partial derivative of the demand curve with respect to price in equation 2, is taken as -123.92. This is equal to the figure used by Green & Vasilakos (2011) scaled up to reflect the growth in demand. Our resulting equilibrium prices imply an average price elasticity of demand of approximately -0.18, which is possibly quite realistic in a 2050 electricity market scenario where demand response technology is more sophisticated than it is at the moment.

The last input is the specifications of the store. These are arbitrary but reflect a wide range of possible round-trip efficiencies, flow constraints, and

demand, and wind turbine output. Intra-day and intra-week profiles are shown in figures 24 and 25, respectively.

[10]See AEA [2011], and DECC Calculator tool: http://2050-calculator-tool-wiki.decc.gov.uk/pages/60.

storage constraints for a future small scale energy store. They are summarised in table 1. Optimal storage strategies were then computed for each of the 245 combinations of these specifications.

Table 1: Storage Specifications

Storage specification	1	2	3	4	5	6	7
Round-trip efficiency (%)	40	50	60	70	80	90	100
Flow constraint (MW)	5	10	15	20	25	30	35
Storage constraint (MWh)	20	40	60	80	100		

Summary statistics of the main variables used can be found in table 9 in the appendix. All prices and costs are in 2012 pounds.

4 Empirical Methodology

In order to estimate energy storage returns we must first have realistic future electricity market prices for the storage firm to maximise over. We therefore estimate a supply function equilibrium for 2050 market conditions. In order to do this we take a realistic starting point for the maximum price and quantity of the SFE and then evaluate the slope of the supply function in equation 2. We then iterate backwards along the supply function by moving along the supply function and re-evaluating the slope until we reach a quantity of 0.

The starting price and quantity we take is the the Cournot equilibrium for 6 equally sized firms with an homogeneous cost function (shown in figure 1). From there, given assumptions on marginal cost and the derivative of demand with respect to price, the slope of the supply function in 2 is then evaluated. This is simplified by the fact we assume 6 equally sized firms with common marginal cost functions. We then assume the supply function takes the form of a linear spline for small changes in quantity. The slope is the reevaluated at this new point further down the supply function and the supply function is then assumed to be linear for this small changes in quantity. This is repeated until a quantity of zero is reached.

We then take the supply function data points in figure 2 and regress price on quantity and its higher orders for each continuous portion in order to calculate the supply function equation. We then pass net demand through this equation to solve for the price at each point in time. This provides us with a realistic time series of market based 2050 electricity market scenario prices for the price taking energy store to maximise over.

The small scale energy storage firm then maximises over this price schedule, for given specifications of the store. In order to do this we use the algorithmic arbitrage maximisation method described in Connolly et al. (2011), and used in Barbour et al. (2014). The procedure maximises profits from arbitrage given specifications of round-trip efficiency, flow constraints, and storage constraints. This is then repeated for all 245 combinations of these three variables. Lastly we estimate how arbitrage revenues are effected by the level of competition in the wholesale electricity market. We do this by repeating the procedure described above for various different numbers of firms.

5 Results

The results section proceeds as follows. Subsection 5.1 presents the results of the supply function equilibrium, and resulting price distributions. Subsection 5.2 presents examples of the storage optimisation algorithm and how the storage firm maximises revenue. Subsection 5.3 shows how storage firm characteristics affect arbitrage revenues and subsection 5.4 shows how varying the level of competition in the wholesale electricity market affects arbitraging revenue.

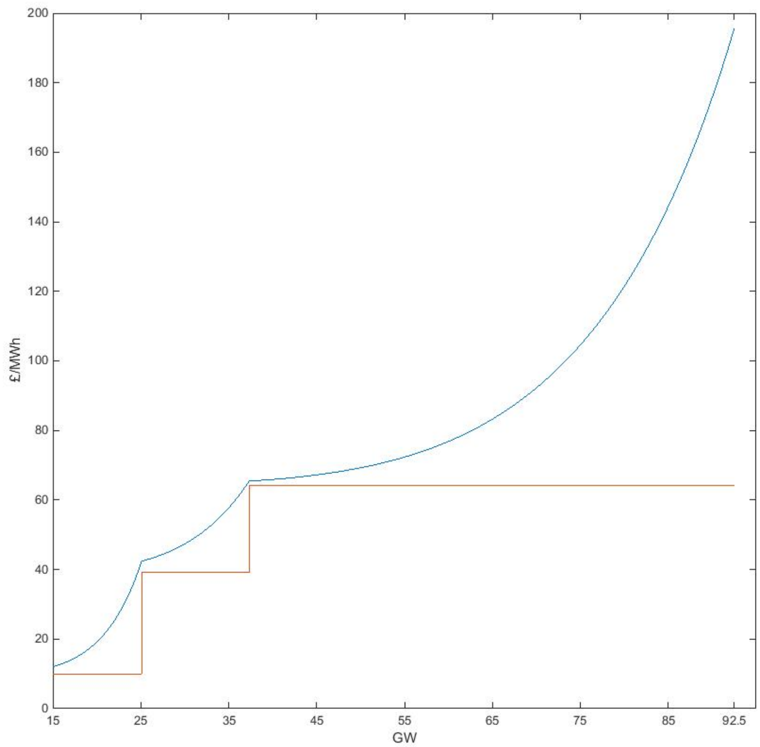
5.1 Supply Function

We estimate the industry supply functions from the best response function (equation 2) and iteratively solve for the slope of the supply function, and equilibrium price. We first take the largest net demand observation as a starting point and compute the Cournot equilibrium. This gives us a point from which to calculate the slope of the supply function in equation 2. We then take a linear approximation of the supply function for a small change in quantity. The equilibrium price is then found from the inverse demand function. The new slope of the supply function is then calculated from the best response function and a further linear approximation is taken. This is repeated until we reach the lowest net demand realisation. Given the large penetration of wind there are some, but not many, hours where net demand is negative. We only estimate the supply function equilibrium over strictly positive values of demand as the supply function equilibrium is only defined over positive realisations of demand. In order to construct future price profiles we generate a mapping between 2050 net demand predictions and the equilibrium supply functions[11].

Figure 1 depicts the resulting supply function and marginal cost function. The supply function in figure 1 is discontinuous where marginal cost increases and the marginal generation technology changes. Markups vary along the supply function and increase with quantity demanded. Indeed, at the very highest level of consumer demand markups reach 300%. However, what matters is

[11] Figures 26 and 27 in the appendix show a time series and histogram of market prices respectively.

Figure 1: Supply Function

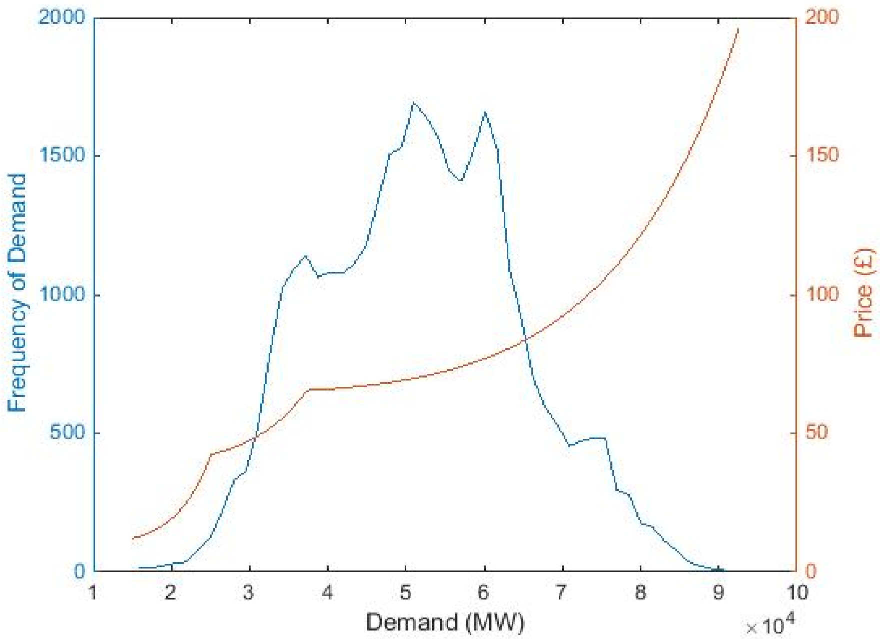


the distribution of demand around the supply function. Figure 2 shows the distribution of net demand along the supply function. We can see that the majority of the time net demand is at relatively low levels of markup. It is only in the extreme right hand tail of the distribution that the supply function increases rapidly. The figure also provides us with an idea of what the storage firm is maximising over.

After passing net demand through the supply function we are left with a time series of equilibrium market prices[12].

[12] Figures 26 and 27 in the appendix show a time series and distribution of the prices the storage firm will maximise over.

Figure 2: Supply Function and Net Demand Distribution

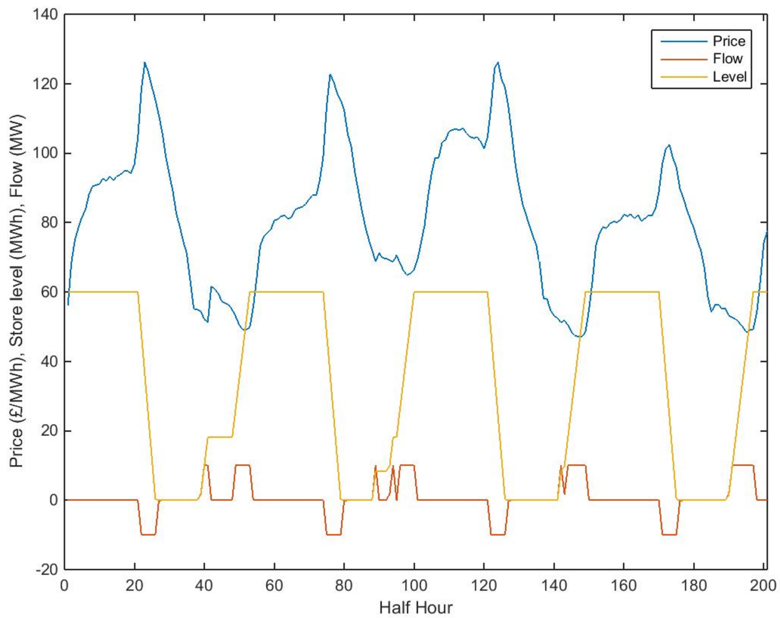


5.2 Storage Optimisation

Optimal storage arbitrage strategies were calculated as per the Connolly et al. (2011) algorithm. This gives us the profit maximising strategies for all different flow, storage, and efficiency parameters. Figure 3 shows what these optimal strategies look like for a sub sample of 100 hours with round-trip efficiency 4, flow constraint 4, and storage constraint 3.

In general the storage unit cycles once per day. For higher values of the round-trip efficiency the storage unit begins to take advantage of smaller price spreads, for example around half-hour 110 in the example above.

Figure 3: Storage Operation



5.3 Arbitrage Returns

Arbitrage returns are calculated for all different specifications of the store [13]. In order to represent these results parsimoniously we run regressions of the profit per year per MWh of storage capacity on the various specifications of the store[14].

Table 2 shows results for the log-log specification:

We can see that round-trip efficiency has the largest single impact on profits. A 1% increase in efficiency (not an increase of 1%) causes a 4% increase in profits. Whereas flow constraint demonstrates diminishing returns. A 1% increase in the flow constraint only results in a 0.36% increase in profit. The negative

[13] see table 1 for the stores various specifications.

[14] For a graphical interpretation see figures 28 through 32 in the appendix for profits over round-trip efficiency and flow constraint for each specification of the storage level constraint.

Table 2: Log Profit Regression

	(1)
VARIABLES	ln Profit
lneff	8.995***
	(0.0608)
lnflow	0.443***
	(0.0146)
lnstor	-0.328***
	(0.0162)
Constant	9.344***
	(0.0778)
Observations	245
R-squared	0.990

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

coefficient on store constraint of -0.248 is more intuitive than it appears since profits are measured as profit per year per MWh of the storage level constraint. Therefore what we are asking is how does increasing the storage level constraint effect profit per MWh of the storage capacity. There are therefore diminishing returns to storage level.

As round-trip efficiency is increased the storage firm is able to take advantage of smaller spreads which would have been unprofitable with a lower round-trip efficiency. As we can see from figure 19 that while netting off renewable output from demand has given us a distribution with longer tails, the distribution is relatively normal. Therefore, as the round-trip efficiency increases, the store is able to increase the amount of hours for which it runs. Table 3 shows the results of the regression of the proportion of the time horizon for which the store is operating (capacity factor) on round-trip efficiency, flow constraint, and storage level constraint. We can see that round-trip efficiency has a large effect on increasing the capacity factor. A 1% increase in efficiency leads to a 2.73% increase in the capacity factor.

As the flow constraint is increased the storage firm is able to capitalise more on given spreads for a given round-trip efficiency and storage constraint. However, they are still limited to maximising over the same spreads since the round-trip efficiency is given, and are still hamstrung by the same storage constraint. Table 3 shows that as the flow constraint increases we actually see the capacity factor fall. This is why we observe this diminishing returns with respect to flow constraint.

Finally, as the storage constraint is increased the store is able to charge and discharge for longer, but is still constrained by the flow constraint for a given round-trip efficiency. Hence the store exhibits diminishing returns with respect to the storage level constraint. It is important to note that while a high capacity factor is generally desirable, it could be that alternative revenue sources from other markets make it desirable to have a relatively low capacity factor so as to be able to take advantage of low hanging fruit in other markets, such as for ancillary services.

Table 4 shows the results for a quadratic specification of the regression. Here we get similar results in that round-trip efficiency has a convex shape and so exhibits increasing returns, whereas flow and storage level constraints exhibit diminishing returns.

See figures 33 through 37 in the appendix for a graphical interpretation of how the three constraints affect operation times.

5.4 Competition

We are interested to discover how electricity arbitraging revenues are affected by the level of competition in the market and to what extent. Intuitively arbitrage revenues should have a direct relationship with the concentration in the market.

Table 3: Log Capacity Factor Regression

	(1)
VARIABLES	ln Capacity Factor
lnefficiency	9.049***
	(0.0801)
lnflow	-0.456***
	(0.0192)
lnstore	0.552***
	(0.0214)
Constant	-1.541***
	(0.102)
Observations	245
R-squared	0.983

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The more competition in the market the less of a mark up is charged over marginal cost. Since markup is positively related to the demand shock observed we should expect a greater markup in times of peak demand than in times of low demand. Limiting competition should therefore increase the spread of prices.

We construct supply functions for varying degrees of competition and optimise storage for each combination of storage capacity, flow capacity, and efficiency specifications. This affects the market by altering the intensity of competition in the market and therefore the resulting equilibrium supply functions. Figure 4 shows, for a subsection of the levels of competition considered, how the supply functions are affected.

From figure 4 you can see that by reducing the number of generators, firms are able to exploit their market power and charge a higher markup. However, this markup is increasing in the quantity demanded. A storage firm should therefore be able to generate greater arbitraging revenues when competition is lower.

Table 5 shows this to be true. Here we regressed arbitrage profits on round-

Table 4: Profit Regression

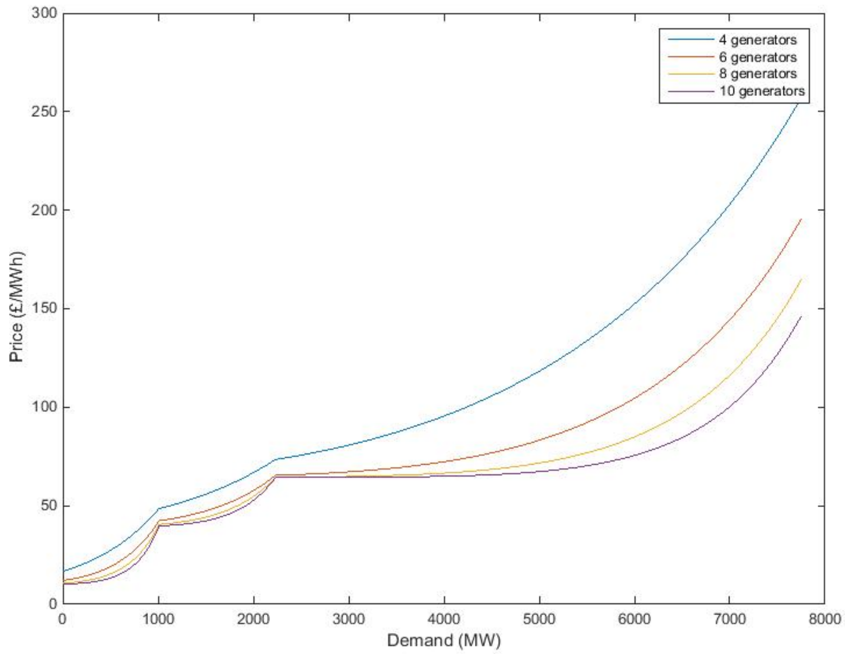
VARIABLES	(1) Profit
efficiency	-132,077***
	(6,959)
efficiency2	97,375***
	(4,248)
flow	196.2***
	(26.15)
flow2	-3.149***
	(0.639)
store	-29.04***
	(10.11)
store2	0.0824
	(0.0827)
Constant	43,972***
	(2,821)
Observations	245
R-squared	0.948

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

trip efficiency, flow constraint, and storage level constraint, and their squares, and dummy variables for each level of competition relative to a base case of 6 firms. Average profit under the 6 firm case is £3,783 per year per MWh of storage capacity over all the specifications considered. We can see that reducing competition to 5 firms is associated with a 49% increase in profits. Whereas increasing competition to 7 firms diminishes profits by 26.7%. This provides us with a reasonable prediction of how arbitraging energy storage firms may be positively or adversely affected by energy market reform, consolidation, or entry.

Arbitrage revenue per year per MWh of storage capacity for all 245 specification combinations of the store are available upon request.

Figure 4: Supply Function Comparison



6 Conclusion

If a low carbon economy based on intermittent generation is to work like ours does currently, then a solution must be found to manage net demand volatility. We explore one of those solutions here: that of technical energy storage. Whilst energy storage technologies are still in their infancy, what is of vital importance to its implementation is for investors and stakeholders, such as policy makers, to have estimates and expectations of future earnings. Furthermore, energy storage technologies come in many guises and have different characteristics. It is therefore useful to have an idea as to the relative return to these various characteristics. That is what this chapter has been focused upon. We provide market founded estimates of the likely revenues an energy storage firm might

Table 5: Log Competition Regression

VARIABLES	(1) ln Profit
lnefficiency	8.747***
	(0.0443)
lnflow	0.319***
	(0.0106)
lnstore	-0.324***
	(0.0118)
2 firms	1.530***
	(0.0269)
4 firms	0.867***
	(0.0269)
5 firms	0.402***
	(0.0269)
7 firms	-0.310***
	(0.0269)
8 firms	-0.527***
	(0.0269)
10 firms	-3.582***
	(0.0269)
Constant	9.630***
	(0.0593)
Observations	1,960
R-squared	0.978

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

make, and provide evidence on the relative return to each of the characteristic of an energy store.

There has been relatively little previous research assessing energy storage's value in a future low carbon GB energy market. However, here we go beyond those previous studies by estimating future energy market prices through a supply function equilibrium. This provides us with a market founded time series of future wholesale electricity market prices over which the store can maximise.

Further to this, we also estimate the relative impact on revenues, in the arbitrage market, of changing an energy store's characteristics, and altering the level of competition in the market. These are elements unique to this study.

Whilst we have focused our attention on profit maximising from arbitrage there are various other services through which an energy store could derive value. These include the STOR market, capacity market, and ancillary services, among others. Further research in this area may try to marry these competing objectives in order to provide overall values of storage. However, what we provide here are robust estimates of one of the potentially more important storage services, especially if technical storage is to play a large part in smoothing net demand fluctuations.

In this chapter we have concentrated on private returns to storage, without taking into consideration the externalities the operation of an energy storage firm might entail. For example, improved security of supply, and lower levels of capital investment in distribution and generation. Combined with future evidence on the social return to storage, our estimates would provide a reliable estimate of the likely scale of subsidy energy storage technologies may need. That is if energy storage costs were not brought down to the levels needed for private investment of energy storage to go ahead.

Stakeholders who may be interested in the research documented in Chapter 1 range from those aiming to reap the rewards of electricity arbitrage, such as potential storage developers, to policymakers aiming to forecast the amount of energy storage installed in future years. Our research demonstrates that under a 2050 energy scenario with large amounts of variable renewable generation the returns to pure arbitrage are still relatively small and are unlikely to provide much of a business case for investment. Under our 6 generator scenario the storage firms on average earned roughly £3,800 per year per MWh of storage capacity across our storage characteristics. As an illustrative comparison, the cost of battery storage is forecast to come down to roughly $100/kWh of storage capacity by 2050 (Rocky Mountain Institute, 2015). Therefore other value streams or subsidy would be essential for storage to be able to be commercially viable in 2050. This would be useful information for potential developers, but also policymakers, including DECC and Ofgem, the energies regulator, trying to forecast the penetration of storage in the electricity market in 2050.

Furthermore, our estimates of the relative returns to each characteristic of storage: flow capacity; storage capacity; and round-trip efficiency give potential developers an indication of the relative importance of each characteristic with regard to energy arbitrage. It therefore provides a further indication of which characteristics are most worthwhile developing.

Table 6: Competition Regression

	(1)
VARIABLES	Profit
efficiency	-137,426***
	(12,868)
efficiency 2	105,592***
	(7,855)
flow	256.2***
	(48.36)
flow 2	-4.211***
	(1.182)
store	-34.91*
	(18.70)
store 2	0.0927
	(0.153)
2 firms	13,325***
	(409.3)
4 firms	4,138***
	(409.3)
5 firms	1,550***
	(409.3)
7 firms	-909.8**
	(409.3)
8 firms	-1,444***
	(409.3)
10 firms	-3,669***
	(409.3)
Constant	42,285***
	(5,223)
Observations	1,960
R-squared	0.698

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Part II

Large Scale Energy Arbitrage, Information Structures and Market Power

7 Introduction

Increasing penetration of low carbon electricity generation technologies inherently leads to increased volatility and uncertainty in energy supply. Increased volatility in net demand poses its own risk to system security, additional costs to conventional generators of frequently ramping up and down, resulting in low capacity factors for these generators. However, it also has the potential to provide opportunities for arbitragers to buy in times of excess supply and sell when generation is scarce.

In a 2050 GB low carbon energy scenario there are potentially very large swings in net demand, lasting for several days at a time[15]. One solution is to have a large amount of fast acting generation capacity, which is used only intermittently. Another solution may be the large scale deployment of energy storage so as to smooth out these large swings in net demand. Previous studies including Grünewald et al. (2011), Drury, Denholm, and Sioshansi (2011), Sioshansi (2011), as well as the previous chapter have sought to establish the likely returns to an energy arbitrager by looking at the operation of a price taking store and estimating its likely returns under a variety of scenarios. However, if there was

[15] Figure **19** in the appendix shows a time series of predicted future demand.

large scale adoption of energy storage then it could end up providing a a large share of power at times of peak net demand. Therefore the assumption that storage is price taking may not be very realistic. We therefore propose a new method of storage profit maximisation which considers how the store is affecting the market price. We do this by characterising discrete market net demand curves at each point in time[16] and having the storage firm maximise over them, given the actions of the generators. See section 9.1 for a description of the large scale arbitrage model.

If we are to try and assess the likely revenues of a storage firm with market power then we must consider what form of competition they are competing under and what information structures are available to the players. Electricity markets have been analysed using several forms of competition including Supply Function Equilibrium (SFE)[17], Bid Function Equilibrium[18] (BFE), and competition in quantities, à la Cournot. Supply function equilibrium, where firms compete in supply functions rather than price or quantity, is generally accepted as being best able to approximate competition in the electricity market by most closely estimating market clearing prices as shown by Willems, Rumiantseva, and Weigt (2009) whereas Cournot competition tends to overestimate prices. However, we are also interested in the information structures available to both generators and the store. Specifically whether each player observes the actions of the other competitors in other periods i.e. whether we have an open- or closed-loop Nash equilibrium[19]. Ordinarily, with exogenous cost functions and market demand there is no distinction between the two - profit maximisation at each point in time would be temporally separable. However, the addition of a

[16]In our example this is at the hourly level.

[17]Klemperer & Meyer, [1989], Green & Newbery, [1992].

[18]See Crawford, Crespo, and Tauchen, [2006].

[19]See Fudenberg & Levine, [1988] for a discussion of the circumstances under which play within these information structures are the same, and under what circumstances they are different.

large scale energy store with market power removes this temporal separability. A conventional generator's strategy today may indeed affect it's own strategy tomorrow through it's affect on the operations of the store. There is then a distinction between these two information structures.

In this chapter we propose a method to estimate the open-loop equilibrium between the store and the conventional generators in the presence of imperfect competition. We then go on to estimate the open-loop equilibrium for a large energy store, and 6 conventional generators using a sub-sample of the data used in chapter 1. We also propose a method to be able to estimate how generators operate under a closed-loop information structure in the presence of a large-scale store with market power. We do not estimate the closed-loop equilibrium as a precise enough approximation to a relatively complex derivative is needed. Subsection 9.2 elaborates in more detail.

In an open-loop model players do not observe the play of others, whereas in a closed-loop model all past play is common knowledge. This leads to players taking very different considerations in an electricity market with a large store. In an open-loop game generators must only consider how their profit at each time period is affected by their strategy today, given the decisions of the store in that period. However, in a closed-loop game the generator observes the past operation of the store, and therefore must consider how their strategy today may affect storage decisions in upcoming periods, and so profits in the future.

Intuitively, a conventional generator will earn the majority of their profits at times of peak demand, and so peak price and higher markups. A large scale storage firm will operate, generally, by charging when generation is cheap, and demand is low, and discharging when generation is expensive, and demand is high[20]. If the store is large enough this will cause the price dispersion to fall,

[20]We only examine the possibility of large scale energy storage acting as a profit maximising arbitrager.

peak prices to be depressed, and off-peak prices to rise. This is not in the generators' interest. If the generators are able to think strategically, as they would under a closed-loop equilibrium, they have the incentive to try to prevent the store from discharging as much in times of peak demand. Intuitively they may do this by withholding supply at times of low demand, thereby narrowing the spread in prices the store takes advantage of. The store would therefore not be capable of producing as much in times of peak demand and so less able to depress the peak prices generators rely on.

In order to be able estimate an equilibrium we must set the players, and these information structures, within a specific form of competition. Of the three alternatives outlined above we choose Cournot competition. We do this because of the tractability of competition in quantities, both theoretically and in its computation. The estimation of strategies for a store with market power is computationally challenging. Cournot makes estimation as tractable as possible.

In defining an equilibrium we must also consider the timing of players actions. All players move simultaneously and so we shall estimate the simultaneous Nash equilibrium for the open-loop model. However, an additional method for finding the simultaneous Nash equilibrium for the closed-loop model is proposed in subsection 9.2 We estimate the open-loop equilibrium via a relaxation algorithm whereby we iterate between the best responses of the generators, and the store until a fixed point is reached. The reason we use a relaxation algorithm is that we cannot analytically find the store's best response function. The storage algorithm operates by taking generator's actions as given and maximising over the remaining net demand functions. We must therefore use a relaxation algorithm to iterate between the generators and the store. On each iteration we are effectively asking the question 'How would the store react to this strategy?', 'Can the generators now improve by altering theirs?'. The equilibrium algorithm is therefore going to proceed by asking the store how it would respond to the generator's strategy, and then computing how the generators would react to that strategy until we reach a pair of stable strategies.

The rest of the paper proceeds as follows: section 8 details the theoretical model for the open-loop equilibrium; section 9 outlines the empirical methodology for estimating the large scale store's strategies, and estimating the equilibrium itself; section 10 describes the data we are using and how it is constructed; section 11 details the empirical results for the open-loop model; section 12 proposes an extension which would allow for the estimation of a closed-loop equilibrium; and section 13 concludes.

8 Model

In this section we outline the theory behind both the large scale store and the Nash equilibrium computation in subsections 8.1 and 8.2 respectively. In subsection 8.1 we shall focus on the large scale store model and the advantages and limitations this implies. In subsection 8.2 we shall describe the open-loop equilibrium, and the relaxation algorithm, the solution concept we shall be using.

8.1 Large Scale Store

The aim of this large scale storage arbitrage maximisation algorithm is to develop a model where the store is not a price taker, but instead will maximise over a series of inverse net demand curves, therefore taking into consideration how the store is impacting the market price. The store is necessarily forward looking since it is trying to maximise arbitrage revenues over a period of time. The storage firm takes the decisions of the conventional generators as given and then maximises over the net demand curves. Subsection 8.2 details how this algorithm will fit within the equilibrium solution concept.

The storage firm maximises the sum of undiscounted profits over the time horizon chosen, given net demand curves, and subject to the usual power, storage capacity, and ramping constraints of a store. That is: the store can only charge/discharge up to a given maximum; at any point in time the store can only have so many MWh in storage; and the store can only increase/decrease charging/discharging by a given amount each period (hour). The storage firm's problem can be defined as follows:

$$\max \sum_{t=1}^{T} p_t q_t^s \tag{6}$$

where q_t^s is the quantity the storage firm either buys (-) from or sell (+) to the market at time t, and p_t is a linear inverse demand function the arbitrager is facing.

$$p_t = a_t - b\left(\sum_{i=1}^{N} q_t^i + q_t^s\right) \tag{7}$$

where q_t^i is the output of generator i in period t, a is the inverse demand intercept, and b is the gradient.

Subject to:

$$\bar{q}^s > q_t^s > \underline{q}^s \forall t \in T \tag{8}$$

$$\bar{L^s} > L_t^s > 0 \forall t \in T \tag{9}$$

$$\Delta q^s_{t,t-1} < \bar{q^s_\Delta} \tag{10}$$

where $\bar{q}^s$ and $\underline{q}^s$ are the upper and lower limits on the store's flow/power constraint, L^s_t is the level of the store at time t, $\bar{L^s}$ is the maximum MWh capacity the store can hold, $\Delta q^s_{t,t-1}$ is the change in power between periods $t-1$ and t, and $\bar{q^s_\Delta}$ is the ramping constraint. There are also a pair of input/output efficiencies: e^{in}, and e^{out} respectively.

We are taking q^i_t as given for all $t \in T$, and therefore what we are doing is taking the partial derivative of the objective function with respect to $q^s_t, \forall t \in T$ and maximising subject to the constraints. That is, we are computing the best-response of the store, given the specific generator strategy profiles Q (but not the best-response function).

In the proposed methodology for computing the Nash equilibrium between conventional generators and the store we are going to be concentrating on two different information structures, namely open- and closed-loop models. Subsection 8.2 will outline both equilibria in more detail, however we shall only be able to consider the open-loop equilibrium for the store. This is due to modeling constraints on the store, which are elaborated on in section 9.1. Effectively, the store is not able to observe the past play of the conventional generators. This means the store will not be considering how their decisions in time t impact the generator's play in future periods. While this is perhaps disadvantageous to the store in a closed-loop equilibrium for the generators (the generators as a result are assumed to have superior knowledge to the store), it is important to note that this game has only become dynamic through the inclusion of the store. The store's strategies and profit making are heavily dependent on the strategies of the generators - they are changing the store's marginal costs and revenues with their play. However, the generator's profits and strategies in the future are only affected by the play of the store in period t through the generators considering how that play affects the the store's strategy in the future. The play of the store in period t, for example, does not directly influence the marginal costs or revenues of the generators in other periods given inter-temporal separability of market fundamentals such as demand curve intercept, slope, and the marginal cost of generation. We can therefore say that these closed-loop considerations of the store are second-order compared with those of the generators.

The maximisation of the store would therefore not have these strategic considerations imposed by a closed-loop information structure. If we were to allow the store a closed-loop model their first-order-condition would be:

$$\frac{\delta\pi^s}{\delta q_t^s} + \sum_{j=1}^{T} \frac{\delta\pi^s}{q_{t+j}^i} \frac{\delta q_{t+j}^i}{\delta q_t^s} = 0 \tag{11}$$

By only allowing the store an open-loop model we are denying them the second term in equation 11. However, the strategy of a generator in period $t+j$ is not heavily dependent on the play of the store in the past period t. It is only through the closed-loop considerations of the generators that the store's actions in period t affect the play of generators in period $t+j$. While it would be interesting to explore these different information structures on the storage side as well, we believe these closed-loop considerations are second-order compared to those of the generators. Furthermore, in a closed-loop model the generators only consider how their actions in period t are going to affect the store's strategy in periods $t+j$ Therefore, q_{t+j}^i should only be an implicit function of q_t^s given the inter-temporal separability of cost functions.

8.2 Nash Equilibrium

If we are to explore the strategies and returns to a large scale store capable of affecting the market price, then we need set the store within a reasonable market framework. This includes the way the firms in the market compete and the type of information structure available to the players in the market. We proceed by formulating the problem, and then go on to describe the two information structures available to the players.

We consider a dynamic game with a finite set of discrete periods $\mathbb{T} = \{0, \ldots, T\}$, and a finite set of players $\mathbb{N} = \{0, \ldots, N, N+1\}$, where there are N conventional firms (generators), and one arbitrager (store) who is able to buy now and sell in the future. The generators, if producing, supply a strictly positive quantity of an homogeneous good (electricity) to the T market demand curves, and the store can both supply and demand to this inverse market demand $\mathbb{P} = \left\{P_0(\sum_{i=1}^{N} q_0^i + q_0^s), \ldots, P_T(\sum_{i=1}^{N} q_T^i + q_T^s)\right\}$, where s denotes the store, and P denotes the inverse market demand function. The firms and store compete à la Cournot. The market demand curve is linear, and it's inverse is specified as $P_t = a_t - b\left(\sum_{i=1}^{N} q_t^i + q_t^s\right)$ given the same definitions of variables as above.

The generators face common, exogenous, time specific marginal costs[21]. The set of which is defined as $\mathbb{C} = \{c_o, \ldots, c_T\}$. The arbitraging store does not face any operational costs, but does face round-trip efficiency of storage e^s. For a given amount of the good bought by the arbitrager only a constant proportion e^s can be supplied in any future period where $e^s \in [0, 1]$.The store naturally a limit on the amount of the good it can store at any point in time, $\bar{s}$, and a limit on the amount it can buy or sell at any given point in time, $\bar{q^s}$. The

[21] A continuous marginal cost function could be used instead, however we simplify the problem by pre-determining marginal cost.

store therefore seeks to maximise undiscounted arbitrage revenue over the time horizon, given the constraints it faces[22]: $\max \pi^s = \sum_{t=1}^{T} P_t q_t^s$ *s.t.* equations 8, 9 and, 10 and round-trip efficiency e^s. Similarly the generators $i \in N$ maximise the sum of their undiscounted profits, $\pi^i = \sum_{t=1}^{T} (P_t - c_t)\, q_t^i$.

Moving onto the information structure of the game. There is common knowledge that all players know with certainty the T inverse demand intercepts, $\mathbb{A} = \{a_o, \ldots, a_T\}$, gradient, b (assumed constant across time), and marginal costs the generators face, $\mathbb{C}$. Furthermore, all players are aware of the existence of each other.

In an open-loop model for the generators they only take into account which time period they are in. For example, all players are aware of all state specific information such as costs and demand functions. They cannot, however, calculate other players previous strategies by say backing it out of the inverse demand function. Each strategy is dependent only on information in the current period t.

In an open-loop model the generators solve the following first-order-condition in each period t:

$$\frac{\delta \pi^i}{\delta q_t^i} = 0 \tag{12}$$

In Cournot competition each player prefers their competitors' output to be low and so if $\delta q_{t+j}^s / \delta q_t^i$ is positive at the open-loop equilibrium q_t^{i*} i.e. less generation today causes the store to produce less tomorrow, say because of a now reduced inter-temporal spread, then the generator's strategic incentive is to, at least locally, to decrease q_t^i (Fudenberg & Tirole, [1991]).

The equilibrium of the game is where both the generators' and store's strategies are mutual best-responses. The Nash equilibrium is where the first-order-

[22] See subsection 8.1 for detail.

condition in equation 12 is satisfied for all N generators in all time periods given a storage strategy profile, which is the argmax to the store's problem in equation 6 (given constraints 8-10), and the generator's strategy profile. Formally:

$$q^i = \arg\max\left(\pi^i\right) \forall i \in N$$

where

$$\pi^i\left(q^{i*}, q^{-i*}\right) \geq \pi^i\left(\tilde{q}^i, q^{-i*}\right) \forall i, \tilde{q}^i \in S^i$$

where S^i is the set of other possible strategies $\tilde{q}$.

It is important to note that the equilibrium is symmetric for all N generators since they face common demand conditions and marginal costs.

In summary, we propose a theoretical equilibrium concept for a large energy storage unit and the conventional generators in the market.

8.3 Equilibrium

In this section we propose a method for finding the solution to both the open- and closed-loop models described above. However, we are only able to estimate one of these equilibria, the open-loop model. It was not possible to estimate a closed-loop equilibrium since we could not estimate a close enough approximation to a relatively complex derivative needed to estimate the closed-loop equilibrium. Subsection 9.2 elaborates in more detail.

In order to find the Nash equilibrium in both the open- and closed-loop models we are going to use a relaxation algorithm to iterate towards the Nash equilibrium. We do not posses the store's best-response function we cannot simply solve the first-order conditions explicitly. Formally, from an initial estimate of the Nash equilibrium, $\mathbf{q_0}$, where $\mathbf{q_0}$ denotes the vector of initial estimates of the Nash equilibrium for each time period, the relaxation algorithm is:

$$\mathbf{q_{s+1}} = (1-\alpha)\,\mathbf{q_s} + \alpha\mathbf{Z}\,(\mathbf{q_s})$$

where $0 < \alpha \leq 1$ is some weighting factor, and $s = \{0, 1, 2, \ldots\}$ is the step or iteration $\mathbf{Z}\,(\mathbf{q_s})$ is the proposed improvement point for the vector of time periods.

The candidate strategy at step $s+1$ is a weighted average of an improvement point $\mathbf{Z}\,(\mathbf{q_s})$ and the current point $\mathbf{q_s}$(Berridge & Krawczyk, [1998]). In step 0 we start with our initial estimate of the Nash equilibrium $\mathbf{q_0}$ which in our case is the Cournot Nash equilibrium for N generators without a store, which is symmetric given the setup. Hence the initial estimate of the Nash equilibrium involves the store buying and selling nothing. We then turn to the store who now reacts to the net demand curves implied by the initial estimate. This is the store's improvement point $\mathbf{Z}\,(\mathbf{q_s})$. We then construct $\mathbf{q_{s+1}}$ for the store.

Now we must construct an improvement point, $\mathbf{Z}\,(\mathbf{q_s})$, for the generators. Their original, initial strategy in now not optimal. The improvement point is therefore constructed by solving equation **??** for the N generators in the market. We iterate between the generators and the store. It is worth noting we can deal with the generators simultaneously since their strategies will be symmetric in equilibrium.

A weighting factor, α is used in order to speed up the conversion to an equilibrium. If α is set too high then what tends to happen is that strategies change too much each iteration and so conversion is slow. It is important to note that the choice of α does not affect the equilibrium we reach, only the speed of conversion. We are not concerned with the speed of conversion and so we select an α equal to 1 for simplicity although more optimal alphas could be chosen to speed up conversion.

Before we estimate this model it is worth asking whether an equilibrium exists to this game and if so, is it unique? Berridge & Krawczyk, (1998) show that there exists a unique Nash equilibrium to which the relaxation algorithm converges if: the strategy space is a convex compact subset of $\mathbf{R}^{N+1}$; the optimum response function $\mathbf{Z}(\mathbf{q})$ is single valued and continuous on $\mathbf{q}$; the Nikaido-Isoda function is a weakly convex-concave function[23]. We do not use the Nikaido-Isoda function in the termination condition, however we do evaluate it upon termination to prove the suggested solution is a unique Nash equilibrium. Subsection 9.2 explains the empirical methodology in greater detail.

9 Empirical Methodology

The empirical strategy is two fold. First we present a large scale storage algorithm for a store with market power, and second we present the equilibrium computation strategy.

If we are to maximise profits of a large store we must first construct an arbitrage maximisation program where the store takes into consideration the effect their input/output decisions have on the market price. This is in contrast to other storage maximisation procedures such as Connolly et al. (2011) which take the market price as given. The storage firm instead faces a demand function at each discrete point in time and maximises profit subject to these[24]. We are

[23]The Nikaido-Isoda function is defined as $\Psi(\mathbf{x},\mathbf{y}) = \sum_{i=1}^{n} [\Phi_i(y_i|\mathbf{x}) - \Phi_i(\mathbf{x})]$ where each summand is the improvement in payoff a player will receive by unilaterally changing their strategy from x_i to y_i while other players continue to play $\mathbf{x}$. The function is everywhere non-positive when $\mathbf{x}$ is a Nash equilibrium.

[24]The net demand functions are predetermined, however the resulting market prices and demands are a function of the equilibrium choices of all the players in the game.

also examining how generators may compete against this large store. There are many information structures we could assume. For example, we could assume generators are unaware of the storage firm: they choose strategies so as to maximise profits, and the storage firm moves afterwards in a Stackelberg game. An equilibrium would therefore involve estimating a Cournot equilibrium for the conventional generators and then maximsing the store over the remaining net demand functions.

Another possibility would be to assume the generators are aware of the store and move simultaneously but seek to maximise their profit at each discrete point in time rather than overall. Generators would not consider how their actions today may affect profit tomorrow, i.e. an open-loop model where we assume generators do not observe the previous actions of the store. However, they are aware of the store and so we would still need to reach a simultaneous Nash equilibrium where the generators choose optimally at each discrete time period subject to the expected actions (which are correct in equilibrium) of the store.

The section will proceed as follows: subsection 9.1 will describe the maximisation procedure for a large storage firm with market power, and subsection 9.2 will describe the estimation procedure for the two equilibria described above.

9.1 Large Scale Storage Algorithm

In order to construct arbitrage strategies for a large scale store with market power we propose a flexible arbitrage maximisation strategy which is capable of maximising over discrete demand functions rather than predetermined market prices, whilst still being subject to the usual constraints on a store such as power, storage capacity, round-trip efficiency, and ramping constraints[25]. In

[25] In the estimation of the equilibrium we shall set the ramping constraint equal to the power constraint for simplicity of estimation. This would be more indicative of operating many small

order to maximise storage returns we use constrained optimisation[26]. This is computationally intensive, however it allows us to be able to specify the market price as a function of storage strategy, and so the effect the storage firm has on market price is internalised. Arbitrage maximisation strategies such as Connolly et al. (2011) would have been faster, and able to optimise over a longer time series, but are not as flexible as the above approach.

We use symbolic math to enter the components of our objective function and perform substitutions inside MATLAB in order to create an objective function which is only a function of the strategy of the store. This new objective function is then maximised with respect to the constraints mentioned above using nonlinear programming. Due to the computationally intensive nature of the maximisation algorithm only 100 observations/hours are maximised over at a time.

9.2 Equilibrium Computation

In order to calculate the equilibrium to the problem (open-loop) we propose the following algorithm. Due to the nature of the store's optimisation program we are going to iterate between optimising the generators, and the store in order to find the simultaneous Nash equilibrium. In the literature this is known as a relaxation algorithm. The algorithm will stop when the sum of absolute changes to the generator's strategy are below an arbitrarily small cutoff point i.e. when we have reached a fixed point. We cannot solve the problem purely by solving a system of first-order conditions since the storage algorithm takes the generator's actions as given when it maximises it's own profits. We must therefore iterate

stores rather than one large store.

[26]Specifically we are going to use fmincon, a constrained nonlinear optimisation tool in MATLAB.

between the two types of player.

We first of all need some starting point to begin our iterative solution procedure. We therefore start with a 6 generator Cournot equilibrium assuming the store is not operating. Six firms are chosen so as to mimic current concentration ratios in the electricity market[27]. This provides us with our initial estimate of the equilibrium, and gives us net demand functions over which the store can optimise (using the algorithm described above). We run the storage algorithm to compute optimal strategies for the store given the generator's actions. We then return to the generator's problem since we have the store's strategy. The generators' initial estimate is now non-optimal as a result, and the generators need to re-optimise.

We now have the store's response to the Cournot equilibrium and so we now turn back to the generators to see how they would change their strategies in response to the store. We then iterate between the two until we reach a mutual best-response.[28].

The generators react to the store's strategy but do not consider how the store may change its actions in future periods if the generator changes its strategy today. We therefore take the first-order conditions for the generators in equation (12) and solve them simultaneously for the 6 generators at each point in time, given the store's strategy. We then return to the store to see if they would behave differently to the generator's new strategy and as such we iterate between the two until the change in the generators strategies is sufficiently small[29].

[27]See Chapter 1 for details.

[28]The condition we choose is that the sum of absolute changes in a generator's strategy is less than 1 MW.

[29] Figure **38** in the appendix shows a schematic for how the algorithm operates.

10 Data

This section describes the inputs to the model. We take a subset of 100 hours from the net demand data collected in chapter 1. For a fuller description of how it was collected and modified see section 3 in chapter 1.

What is needed for the model is a series of demand functions for the store and generators to maximise over, and therefore we need a series of inverse demand function intercepts, and the slope of the inverse demand function at each point in time[30]. We are therefore going to back out the intercepts to the inverse demand functions from a supply function equilibrium (SFE) for a 2050 GB electricity market scenario. The SFE provides us with price, quantity pairs where we can then calculate the inverse demand intercept for a given slope of the demand function. These provide the store and generators with inverse demand functions at each point in time for them to maximise over.

In order to calculate a supply function equilibrium for a 2050 scenario we must have a belief over future demand profiles. We therefore take aggregate GB electricity demand data at the half-hourly level between the 1st of January 2011 and the first of January 2013 and scale this up to 2050 levels in line with the central predictions of Ault [2008]. This equates to 1.1% compound growth per year. However, we do not alter the profile of demand. Predicting aggregate consumer demand profiles (both daily and seasonally) is beyond the remit of this paper. Furthermore an assumption on the shape of daily or seasonal demand would drive prices and associated storage operations and revenues too much for comfort. While potentially unrealistic all that is important to an arbitrager is the variance and timing of demand. If these remain roughly the same then our results are still valid.

[30] We assume the slope of the demand function is constant, however it would be a trivial extension to make the slope vary over time.

We do, however, want to take into account potential future net demand volatility generated by the increased penetration of renewables. By 2050 40% of the UK's electricity needs are set to be supplied by renewables (DECC, 2011). We therefore need some belief over half hourly hourly renewable energy production. We therefore take national grid metered wind turbine generation [31] for the the same time period. Wind turbine generation is then scaled up to 2050 installed capacity levels. Wind turbine generation is then netted from demand. This provides us with the net demand profile to be met by generators.

In estimating the supply function equilibrium we must have a belief on the composition of electricity generation in 2050 and so the marginal cost of generation. We take DECCs MARKAL 3.26 analogous scenario for 2050 which includes a scenario for the future composition of generation. The corresponding marginal costs are taken from National Grid (2012) which include CO_2costs priced at 2050 carbon prices. These are used both in the supply function equilibrium and the open-loop equilibrium estimated in this chapter.

Finally, the slope of the demand function, i.e. the partial derivative of the demand curve with respect to price, is taken as -123.92. This is equal to the figure used by Green & Vasilakos (2011) scaled up to reflect growth in demand.

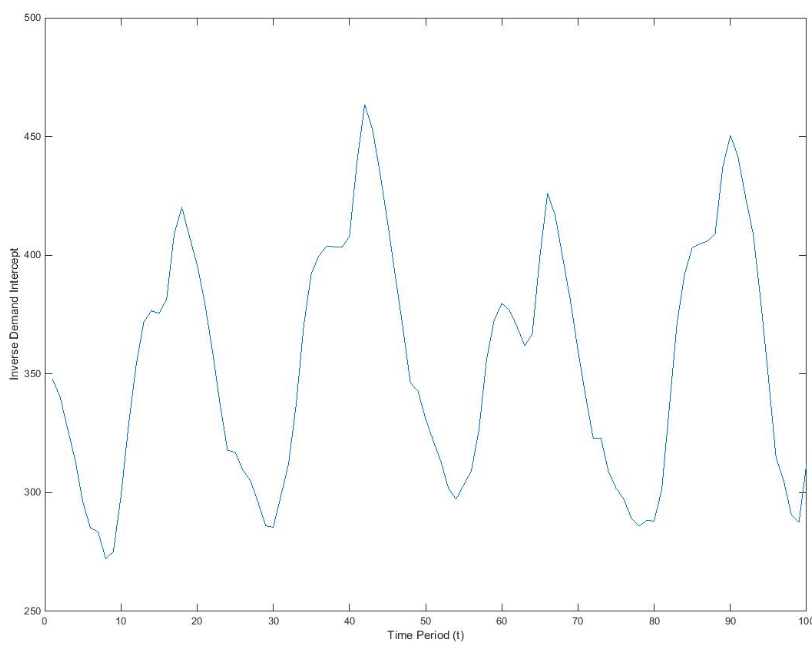
We then use this data to calculate an equilibrium supply function described and presented in chapter 1. We then pass the net demand data through this supply function to get our price, quantity pairs. Inverse demand intercepts are then calculated for the given slope of the demand function. See figure 5 for the time series of inverse demand intercepts.

The round-trip efficiency of the storage firm was set at 70%. We then set the flow constraint, and storage level constraint at very high levels which were not binding in equilibrium. Effectively the equilibrium presented below is an unconstrained equilibrium We did this because we wanted the store's operation

[31] Data on other types of renewable generation were not available for the whole period.

to be limited by the market and how much they can buy and sell to maximise profits, rather than an arbitrary flow constraint or storage constraint. If we were using a price taking arbitrage model then in the face of unconstrained flow and storage constraints the store would choose to store as much as they could (an infinite amount) when prices were low and then discharge it all when the price increased, given the spread in prices was greater than the round-trip efficiency. This completes the inputs necessary for us to calculate the open-loop equilibrium.

Figure 5: Inverse Demand Intercepts



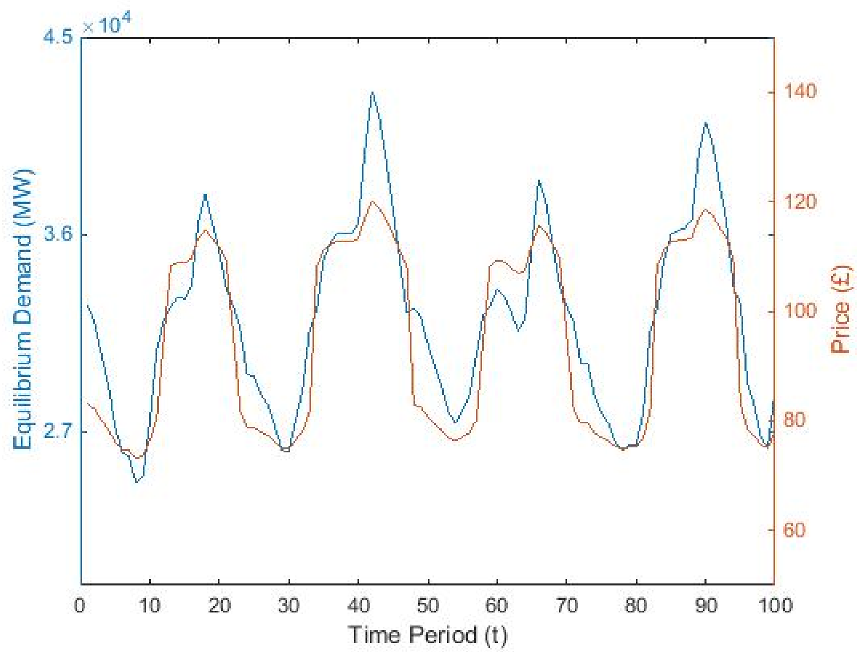
11 Results

We estimate the open-loop equilibrium between conventional generation firms and a large store. Generators are only able to observe the time period in question, and so any state specific variables.

The results section proceeds as follows. Subsection 11.1 describes the open-loop equilibrium. Subsection 11.2 then provides details of the convergence in strategies.

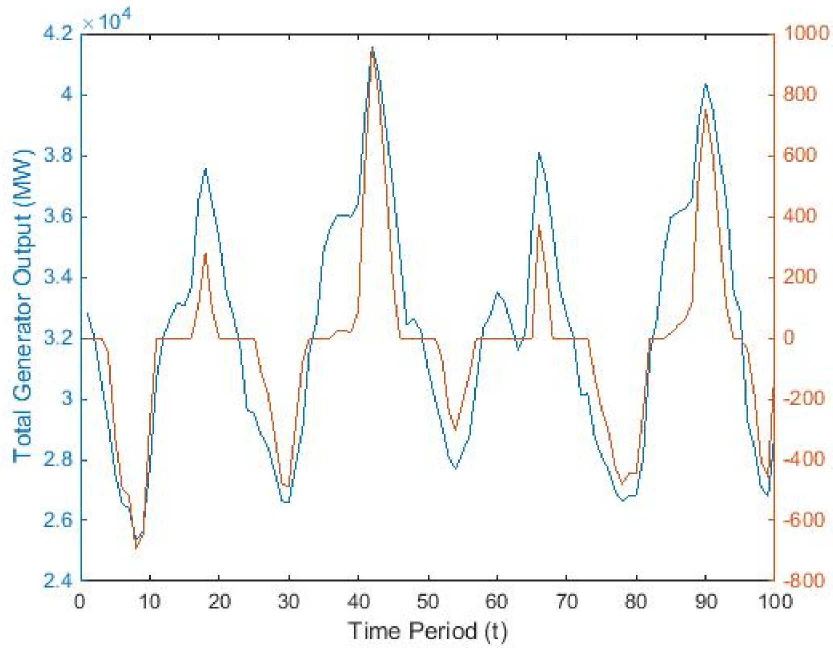
11.1 Open-loop Equilibrium

Figure 6: Open-loop Nash Equilibrium Demand and Prices



We estimate the open-loop equilibrium for the 100 hours of inverse net de-

Figure 7: Open-loop Conventional Generation and Storage Strategy

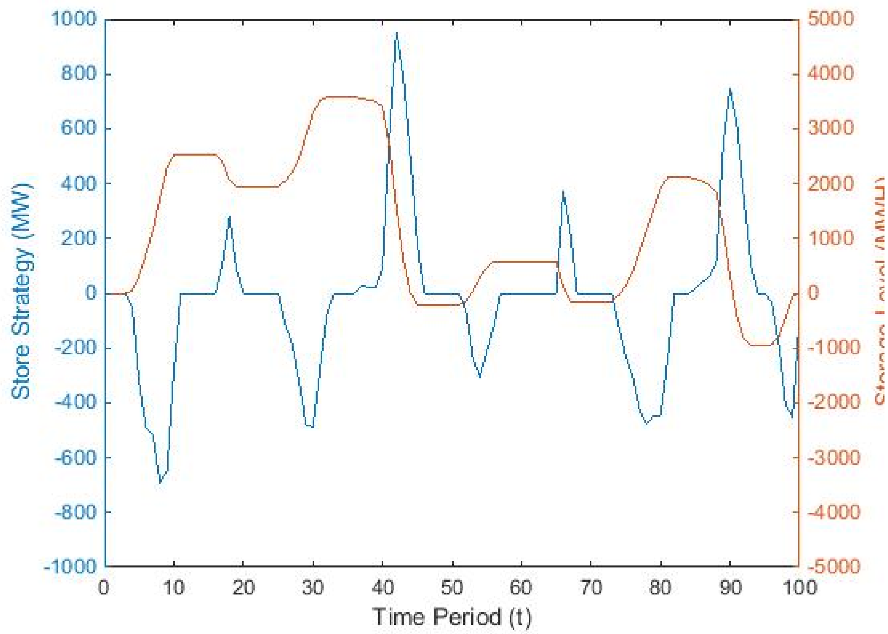


mand functions described above. The resulting market clearing demand and prices are shown in figure 6 and the familiar diurnal profile of demand over the four days of data can be clearly seen. The average price across the 100 hour sample was £94.5/MWh[32], and the average demand/supply was roughly 32 GW. While this may seem a little high, the demand fundamentals were taken from mid-winter and so prices and quantities should be relatively high. Furthermore, we were using Cournot competition and this tends to overestimate prices[33]. Figure 7 shows the output decisions for both the conventional generators and the store, and figure 8 shows storage flow and storage level over the 100 hours. We can see the store is charging (negative storage output) when price and demand is low, and then discharging when the price increases. Like the small store results in chapter 1, the store cycles roughly once a day. Over

[32] Valued in 2012 pounds.

[33] See Willems, Rumiantseva, and Weigt [2009].

Figure 8: Open-loop Storage Strategy and Storage Level



the sample period of 100 hours the store was able to earn just £62,844. Over a year that could equate to £5.5m. This is very low given the size of the storage operations observed. One limiting factor of course is that the store only cycles once per day and spends several hours per day idle. These results are, however, for a relatively low round-trip efficiency of 70%. The store could expect to earn much more if round-trip efficiency were raised, as suggested in chapter 1.

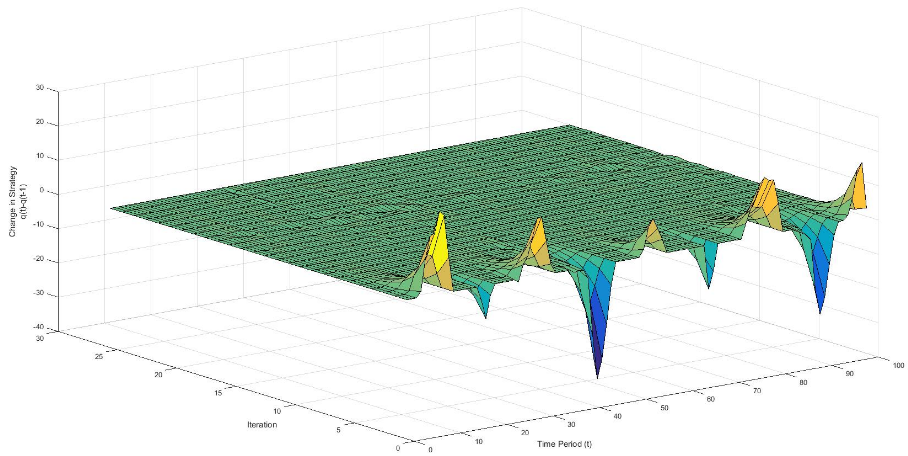
The store's flow and storage level constraints were set so that the storage firm was unconstrained in equilibrium[34], however we can see that storage never discharges more than 1 GW per hour and never charges more than 0.8 GW per hour. Furthermore, the storage level never goes above 4 GWh. Whilst these are very large quantities it shows that there is natural limit to how large energy storage can be and maximise arbitraging profit.

[34]See section 10 for details.

In this analysis we have been assuming that the store is operated by one firm and so can be thought of as a quasi-monopolist in arbitrage. Of course they are not monopolists in the market overall since there are 6 other conventional generators also producing the same homogeneous good. However, had we split the store up in to several competing firms we may have found that we got slightly more demand shifting (charging and discharging), as you would expect in Cournot competition. Of course the limiting factor here on how much demand shifting is possible is the round-trip efficiency of the stores.

In assuming an extremely large energy store who is only bounded by the market we are ignoring the possibility of a market derived size of energy storage. We mention above that the storage operations observed here give an indication as to the maximum size of a store. However, there are a number of reasons to think that this may be an upper bound on the size of energy storage. We do not include the payment of any taxes for the store buying/selling electricity. This would result in the store effectively having an lower round-trip efficiency than it technically does. Furthermore, we have not included any operational costs which would again be equivalent to lowering the round-trip efficiency. Finally, we have not considered any capital costs or required return on investment for energy storage. It is therefore quite likely that the store would be smaller than implied by the storage operations. Since the store is effectively pushing the spreads together by increasing demand off-peak and lowering it on-peak it is likely that the larger amounts of demand shifting would not be generating enough profit to cover capital costs. Indeed the relatively small arbitrage revenues we observe here are suggestive of energy storage being better off taking advantage of low hanging fruit at smaller quantities and keeping capital costs to a minimum.

Figure 9: Open-loop Generation Strategy Convergence

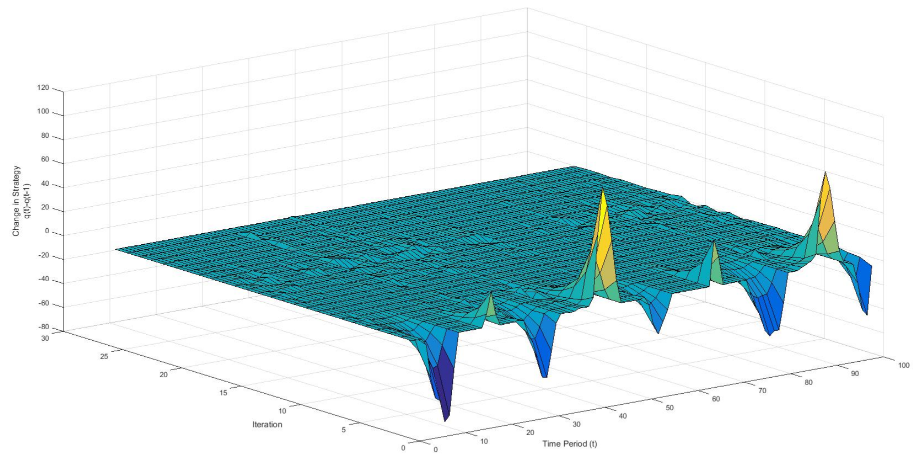


11.2 Convergence

Figures 9 and 10 show the strategy convergence for conventional generators, and the energy store respectively. The Y axis depicts the change in strategy between iterations, the X axis shows the iteration number, and the Z axis shows the time period (1-100). For both types of players we can see that most of the convergence occurs in the first few iterations. Convergence is only as protracted as it is here because we chose a very low strategy change value for the definition of a fixed point.

The initial generator strategy is for them to produce the Cournot equilibrium for 6 symmetric firms. In the solution strategy the store then responds to the 6 firm Cournot outcome. In response to the store's strategy the conventional generators then reduce their output in periods of peak demand and increase their output in times of low demand. This reflects the fact that the store is increasing demand in low demand periods by charging up the store and is lowering net demand at peak times by supplying to the market and so giving

Figure 10: Open-loop Storage Strategy Convergence



generators less incentive to produce during peak demand and more incentive to produce off-peak.

The energy store converges by slowly increasing the amount they are charging and discharging as the conventional generators produce less and less at peak times. Here the negative numbers on the energy storage convergence graph show that store is increasing their demand/charging. Positive means the store is increasing its discharging/supply. These graphs give us an idea of how much we may underestimate a large store's output if we were not to compute the Nash equilibrium but rather have the energy store move second in response to a Cournot equilibrium.

12 Closed-loop Extension

In this section we propose a closed-loop extension to the open-loop model outlined above. Much of the theory and practical estimation remain the same, the

the small addition of closed-loop strategic considerations where applicable.

12.1 Closed-loop Equilibrium

The theoretical model behind a closed-loop equilibrium is much the same as for an open-loop equilibrium, as described above. This only affect the generators since we have already established that the store, although it is forward looking, does not consider how its actions today may affect the play of the generators in the future. The store is always in an open-loop model.

We make the distinction between open- and closed-loop equilibrium because a large scale energy store can make the problem a dynamic one where the generators actions in time period t can affect the play of the store in future periods. The closed-loop equilibrium addresses this dynamic aspect to large scale energy storage whereas open-loop assumes it away by limiting the amount of information available to the generators, meaning they would not make strategic decisions in period t in order to influence play in the future. Due to limitations on the ability to maximise an arbitragers profits we limit the store to the open-loop model, as described above. The store is still necessarily forward looking since they are maximising arbitrage revenues over time, however they do not consider how their actions today may affect the play of competitors in the future.

A closed loop-equilibrium follows what is described in subsection 8.2. In a closed-loop model all past play is common knowledge. Generators now have the information to act on the strategic incentive to decide current play so as to influence the future play of their opponents. Generators $i \in N$ therefore seek to maximise profits given these strategic considerations and will therefore solve the following first-order-condition in each period t:

$$\frac{\delta \pi^i}{\delta q_t^i} + \sum_{j=1}^{T} \frac{\delta \pi^i}{q_{t+j}^s} \frac{\delta q_{t+j}^s}{\delta q_t^i} = 0 \forall i \in N \tag{13}$$

For a given period t the generators recognise that subsequent period actions depend upon their actions in period t through the response of the other players (here the store). As such the generators now have an extra term in their first-order-condition, which encapsulates their strategic incentive to alter actions today so as to influence competitors play tomorrow.

In a closed-loop equilibrium, the Tth periods actions, after actions in the set of periods $\mathbb{T} = \{1, \ldots, T-1\}$ have been realised, must be a Nash equilibrium of this stage game (Fudenberg & Tirole, [1991]). As such the players are only forward looking in their assessment of how changes in strategy today affect play tomorrow. Threats of future play are not something considered in a closed-loop model.

For the closed-loop model the Nash equilibrium is where the first-order-condition in equation 13 is satisfied for all N generators, in all time periods, given a storage strategy profile, which is the argmax to the store's problem in equation 6 given constraints 8-10, and the generator's strategy profile.

12.2 Equilibrium Computation: Closed-loop

In order to estimate a closed-loop equilibrium we follow much the same process as for the open-loop case outlined above. Here the generators seek to take into consideration how their generation decisions today influence storage strategies in the future, and so the profits of the generators in those future periods. We can think of the generators as now maximising total profits, rather than profits at each point in time. Players move simultaneously and so we estimate a closed-loop simultaneous Nash equilibrium between the generators and the store.

In a closed-loop equilibrium the generators are considering not only how profit at time t is affected by output in time t but also how it is affected by strategies in periods $t-j$ i.e. how profit in time t is impacted by the store's choices in time t, which are a function of the generator i's strategies in earlier periods q^i_{t-j}. This means we have an extra component of the first-order condition to consider, as specified in equation **13**. We can solve for $\delta\pi^i_t/\delta q^s_t$ analytically and so this does not present a problem. However, given the nature of the store's maximisation procedure we cannot take the derivative $\delta q^s_{t+j}/\delta q_t$ explicitly from the store's best response function, and must instead take an approximation. In order to do this we would generate alternative generator strategies by taking the generator's previous strategy and making a small change in each time period. For a T period problem we therefore have T alternative generator strategies. The storage algorithm would then be run for each of the alternative generator strategies, and we would approximate the partial derivative in **13** by taking $\Delta q^s_{t+j}/\Delta q_t$. We then construct the first-order conditions in 13 and solve them simultaneously as in the open-loop case. We then return to the store and see how it would respond to this new generator strategy. We would then proceed to iterate between the generators and the store until the change in the generators' strategies is sufficiently small, and a mutual best response is reached[35].

When we tried to compute the closed-loop equilibrium we were able to reach a fixed point. However, on closer inspection of the results the approximation of the partial derivative in **13** was not good enough, which resulted in some unusual activity from the generator. For example, they over produced at times of low demand and under produced in times of peak demand. This runs contrary to our intuition outlined above, and furthermore the generators were found to

[35] Figure **38** in the appendix shows a schematic for how the algorithm operates for both the open- and closed-loop models.

make less profit in the closed-loop case than the open-loop. This is unusual since we are giving the generators more information in the closed-loop case. Future research may aim to better approximate the partial derivative in question, or possibly explicitly solve for it.

13 Conclusion

In this chapter we have proposed a new method for maximising a large arbitraging energy store with market power. We have also proposed a methodology for calculating the Nash equilibrium between a large energy store with market power, and conventional generators. We have done this for two different information structures: open-loop models, and closed-loop models and have been able to compute the simultaneous Nash equilibrium for the open-loop information model. Previous analysis of large scale energy storage, such as Grünewald et al. (2011), has not been market focused, or tried to address the market power a large scale store would have. We do so here by using a flexible maximisation program for the store, and a relaxation algorithm to converge towards a simultaneous Nash equilibrium. This is an important development of the research around energy storage. By making an open-loop information assumption it gives us the tractability to be able to estimate an equilibrium with market power. Furthermore, uncertainty in the energy market may make it infeasible for generators to make the kind of higher order, strategic, considerations we propose in the closed-loop equilibrium. Therefore, the open-loop equilibrium may indeed be a better approximation of reality.

Our calculation of large scale energy storage strategies show us that, for the time horizon studied, the energy store never discharged more than 1 GW per hour, never charged more than 0.8 GW per hour, and the storage level never exceeded 4 GWh. This provides an indication of the natural limit to the size on an energy storage unit. Whilst we estimated storage revenues for a relatively low round-trip efficiency of 70%, the revenues earned by the store are not encouraging. Over the sample period the store was able to earn just £62,844. For various reasons, such as capital costs, it is likely that energy storage would be even smaller than implied by the operation of the store here. If large scale energy storage were to provide positive externalities not valued in the wholesale electricity market we estimate here, then either a subsidy or an explicit pricing of that externality may be needed for large scale energy storage to become viable.

Further research may try to estimate more precisely the partial derivative in equation **??**, which proved a stumbling block in estimating a closed-loop equilibrium. Given the computational difficulty in finding the equilibria described above, we only demonstrate results for a small sample of 100 hours, for a given round-trip efficiency, and unconstrained storage level and flow constraints. Further research may therefore try to estimate storage arbitrage earnings for various different specifications of the store.

Key stakeholders who may be interested in the research documented in Chapter 2 are academics trying to incorporate large amounts of energy storage into a model of the energy market, potential developers of energy storage, and policymaker, including DECC and Ofgem. In this chapter we have provided a method for estimating an equilibrium in an energy market characterised by Cournot competition with a large amount of storage. Previous research neglected the impact storage firms can have on the market price, and resulting strategies of conventional generators. Given that energy storage is projected to reach relatively high penetrations academics and policymakers alike would benefit from analysing energy storage in a non-cooperative game theoretic setting

[36]. Furthermore, we propose a method for extending the analysis to include a close-loop equilibrium where firms can strategically set quantities to affect storage strategies in future periods, which would present a step forward in the analysis of large scale storage.

[36]See National Grid (2016) for an example of future energy scenarios with a large volume of storage capacity.

Part III
Residential Electricity Time-of-Use Tariffs: A Welfare Analysis

14 Introduction

The increased penetration of variable, non-dispatchable renewable electricity generation poses greater stress on the system operator to balance supply and demand potentially leading to higher prices for consumers. In response to this increased volatility commentators have recommended several courses of action including energy storage, super-grids, and demand response. Currently, residential electricity tariffs provide little incentive for consumers to smooth out consumption as residential electricity tariff structures pose little resemblance to the true cost of providing power. In the UK domestic consumers generally face a standing charge and either a single (e.g. flat-rate) or differential tariff (e.g. economy 7), which is either fixed or variable. Some economists argue that time-of-use tariffs would raise efficiency and lower the cost of meeting electricity demand by aligning the marginal cost consumers face with the marginal cost of generation (Kahn, 1979 and Joskow & Wolfram, 2012).

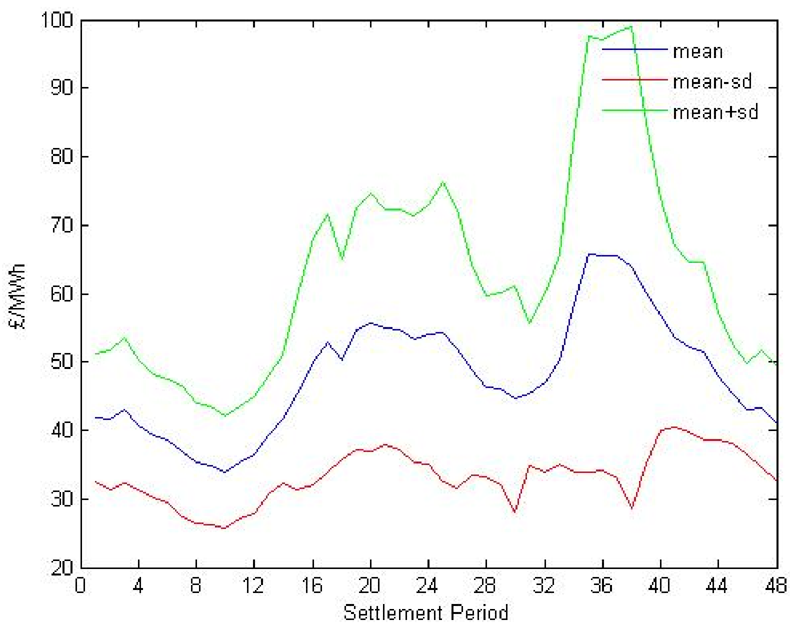
Figure 11 shows the average UK system sell price in 2014 for each settlement period[37], plus/minus one standard deviation[38]. We can see that the system sell price can vary substantially during a day, however consumers face very little price volatility themselves and so are given little incentive to smooth out their consumption.There are three main reasons why the cost of generation changes throughout the day. Firstly, generation generally follows a merit order where low marginal cost, inflexible base-load generation (such as a nuclear power station)

[37] Settlement periods are at 30 minute intervals throughout the day.

[38] Data collected from Elexon. See: www.elexonportal.co.uk/article/view/249?cachebust=zhlw7849gb.

operates largely continuously. This provides enough power to meet base-load demand. Shape to the daily demand profile is then provided by higher marginal cost, but more flexible, generation such as gas. Secondly, there are constraints on the transmission of electricity which may result in either extra line-losses or less efficient generation being used to service demand. Thirdly, unforeseen failures of both generation and transmission capacity can change the marginal cost of generation significantly. However, although the cost of generation can vary quite substantially throughout a day, consumers electricity tariffs do not reflect this very well.

Figure 11: System Sell Price: Average per Settlement Period



One solution to this problem is to align the incentives of consumers and generators by giving consumers prices which reflect the true cost of meeting their demand. Time-of-use (TOU) electricity pricing and real time pricing[39]

[39]In this chapter "TOU" will be used to mean the general class of electricity tariffs where

has attracted much attention from academics as a potential means to reduce peak demand and so address the engineering and environmental challenges of meeting volatile net demand. Jessoe, Rapson, and Smith (2012) demonstrate evidence as to its effectiveness. They show that households who are switched on to a TOU tariff reduce their electricity consumption substantially during peak periods. Using a field experiment Jessoe and Rapson (2014) go on to show that informed households with TOU pricing not only reduce demand during peak pricing periods but also after, suggesting evidence of habit formation, and spillovers. Wolak (2006) also uses a field experiment to attempt to find evidence of TOU pricings effectiveness. He finds that consumers do respond to price changes, but only on days where they are given pricing information, and so shows little evidence of habit formation. There are therefore still questions as to the exact size and consistency of consumer response to TOU pricing. Jessoe, Rapson, and Smith (2013) find evidence that consumers can react unusually to pricing information. Indeed they found consumers reduced their consumption in the face of lower electricity prices suggesting other factors aside from price are also important to consumers.

Schofield et al. (2014) investigated the potential value of residential demand response from a demand side response trial which took place in London during 2013, Low Carbon London (LCL). A subset of the programme were given ex-ante revenue-neutral dynamic time-of-use prices (dTOU) with prices ranging from £0.04/kWh to £0.67/kWh. They found consumers were incentivised to change their electricity consumption in reaction to changes in the tariff. Over the course of the trial year 95% of households saved money relative to what they would have spent. They further found that peak demand was reduced by 10%, with more engaged households showing a reduction of 20%. Indeed, they did find

consumers bay a different rate at different times of use, including real time, conventional TOU, and dynamic pricing such as critical peak pricing.

a significant amount of variation in engagement between individual households. The LCL trial also found that the amount of engagement was unrelated to any of the socio-economic indicators which were available to them.

Faruqui (2010), documents further evidence on potential gains from dynamic tariffs. The New York Independent System Operator expected to find similar results to Schofield et al. (2014) where peak demand was expected to fall between 10-14% on the universal deployment of real time pricing. Furthermore, Faruqui and George (2005) find in analysing the results of California's Statewide Pricing Pilot that consumer response to TOU rates are highly dependent on peak-to-off-peak price ratio. Ratios of around 2 to 1 find results of roughly 5%. Whereas 5 to 1 and 10 to 1 ratios produced reductions of between 8 and 15% with no enabling technology i.e. smart meters, and between 25% and 30% when paired with enabling technology. However, they did find that responsiveness varied with climate zone, air-conditioning ownership, and other customer characteristics.

The Irish Commission for Energy Regulation conducted a largest, and statistically robust smart metering behavioural trial to provide information on the impact of smart metering initiatives on consumers. Involving roughly 5,000 consumers, who were given up to 4 price bands in a day, they found that the deployment of TOU tariffs in combination with other stimuli, including financial feedback, resulted in changes in energy consumption. Residential trial participants reduced energy consumption both overall and at times of peak demand. Indeed, for consumers with TOU tariffs, and demand side management stimuli, overall electricity demand was reduced 2.5%, and peak usage by 8.8%. Those receiving a bi-monthly bill and with access to a smart meter were found to reduce peak demand by even more (11.3%). They further found that reductions were correlated with usage i.e. high usage households reduced consumption the most.

In addition, Carroll, Lyons, and Denny (2013) further analyse the Irish smart meter trial and find evidence that providing information and feedback acts mainly as a reminder and motivator for those under TOU tariffs. They find that feedback significantly increases consumers knowledge of their electricity usage, however improvements in knowledge are not correlated with demand reductions.

Di Cosmo, O'Hara, and Devitt (2015) further analysed the results of the Irish smart meter trial. They find that while the TOU tariffs reduced peak demand, the most reliable reductions in demand were achieved by those consumers with in-house displays and were provided financial feedback through them. Whereas bi-monthly billing provided the least reduction. They also used information on consumers educational attainment and showed that those consumers with higher levels of education used the information associated to the TOU tariffs slightly better than the average.

Gans, Alberini, and Longo (2012) however, find that the provision of information produces large declines in electricity consumption. They analyse a natural experiment in Northern Ireland where standard prepayment meters were replace with smart meter providing real-time data on consumption. They show that as a this caused a decline in electricity consumption of between 11-17%.

Although TOU tariffs can be effective, as demonstrated above, not all TOU tariffs are created equally. Faruqui and George (2002) demonstrates that dynamic pricing, where either the size of the price change, or the timing, are set by system demands, can be much more effective than conventional TOU pricing. However, they show that net benefits can vary significantly with the characteristics of the customer base, the cost curve applying to the industry, and the behavioural patterns of the consumers.

Faruqui and Sergici (2009) survey the experimental evidence on household response to dynamic electricity pricing. They survey evidence from the, as of then, 15 most recent experiments with dynamic pricing of electricity. The document conclusive evidence that households respond to higher prices by lowering demand. The magnitude of price response depends on several factors, including the magnitude of the price increases, whether the household has air-conditioning, and enabling technology, including smart meters. Across the experiments studied TOU rates tended to induce between a 3-6% drop in peak demand. Whereas critical-peak pricing tariffs induced drops between 13-20%. Furthermore, when these are accompanied by enabling technologies critical-peak pricing induced reductions of between 27-44% in peak household demand. This is also corroborated by Faruqui, Hledik, and Palmer (2012), who show that load shifting increases with the size of the price signal but at a decreasing rate,

Despite the questions about TOU tariff efficacy, there are potentially important concerns relating to the equability of such a policy (Faruqui, 2010). One particular concern is that TOU tariffs may be regressive in nature. For example, low income, low use households may only use electricity when it is needed the most, and so at times of peak demand and peak price under a TOU tariff. In this way they may lose out relative to high use consumers. Research by Horowitz and Lave (2012) discovered this to be the case in Chicago. Alternatively low income household may have less energy efficient appliances and so may have higher electricity consumption relative to high income households and so be hit harder by peak pricing.

Faruqui, Hledik, and Palmer (2012) shows that each design of TOU tariff can produce different degrees of price volatility and uncertainty for consumers. Furthermore, there could be a loss of welfare associated with reducing usage during high price periods, or indeed with the hassle of shifting consumption to lower price periods.In this paper we therefore aim to explore what would be the effects such a tariff structure on consumer bills, and who would win and who would lose out as a result.

We propose three revenue-neutral tariffs in the spirit of Borenstein (2013) whereby consumers would on average have the same bill whether they opted for a TOU tariff or not. The tariffs are designed to reflect the true cost of supplying electricity to the consumer and so are based upon the average system demand for each settlement period in 2014. For the reasons mentioned above electricity prices tend to be higher at times of peak demand as so we use it as a proxy for the true cost. Section 16 explains in detail how we arrive at each of the tariffs.

We then apply these tariffs to the individual household consumption data in the HES and arrive at household specific spends over the period they were observed. We then scale these up to give us a yearly spend under each proposed tariff. We then compare each household's proposed spend with how much they would have spent under a flat-rate tariff. We then perform analysis on the distribution of winners and losers - specifically looking at how consumers are affected by average use, and social indicators. We also explore how this changes when some degree of demand response is incorporated.

15 Data

The remit of this research is to construct three TOU tariffs and analyse the welfare implications of each. All three are based on average Great Britain (GB) aggregate system demand and will take the same shape. Therefore when average GB system demand is low the TOU prices shall also be low. In order to do this we first need information on the data underlying the three proposed tariffs.

Great Britain aggregate system demand data at settlement period level is used from the National Grid[40]. Figure 12 provides an illustration of the the average system demand per settlement period.

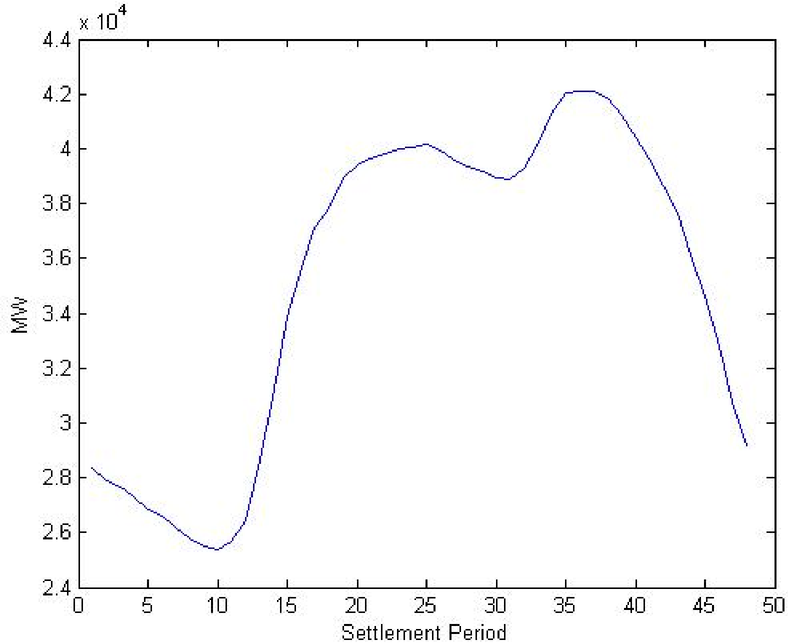
Residential consumption data is used from the Household Electricity Survey (2013)[41]. The HES surveyed households at various different levels from individual appliance up to overall household demand, and different levels of regularity from half hour upwards. Overall, 224 households were observed continuously at the half hourly level. On average each household was monitored for 343 days[42] which gives us a representative sample of how households shall be affected across the year. The relatively small sample size however means that we could not say anything about demand differences and so bill differences across the year and so we could not base our tariffs on seasonal variations in demand. However, we do look at average residential demand at the settlement period level.

The diurnal average demand in figure 13 was then used to construct revenue-neutral residential electricity tariffs. Subsection 16.2 explains in detail how this was performed.

In order to perform distributional welfare analysis the HES supplies us with a rich set of information on the households being surveyed. This includes social class, household type, the number of rooms in the property, and the number of electrical appliances in the household among others. Unfortunately the HES does not provide us with information of the respondents incomes, however we are able to use the indicators listed above as a proxy for income/wealth and can build up a picture of who may be affected by TOU tariffs, by how much, and what the variance in bill change from flat to TOU may be i.e. are some households severely adversely/positively affected by a change to TOU tariff?

[40]See National Grid (2015).
[41]See HES (2013).
[42]See figure 39 in the appendix for the distribution of household observation length.

Figure 12: Average GB Electricity Demand (MW)



Finally, the baseline flat rate tariff is given as 20 cents per kWh, taken from International Domestic Energy Prices (2015) from the Department of Energy and Climate Change (DECC)[43]. We retain the use of cents and dollars so as to make the results easily comparable between countries.

15.1 Household Electricity Survey Consumer Profiles

In this section we provide some summary information on the Household Electricity Survey and the households they observed. The Household Electricity Survey was conducted over 2010 and 2011, and was published in 2013. In total there were 224 households who participated in at least half hourly monitoring.

[43]See https://www.gov.uk/government/statistical-data-sets/international-domestic-energy-prices.

On average each household was observed for 344 days with a minimum of 198 days of observation, and a maximum of 778 days of observation. The standard deviation of observation length was roughly 85 days[44]. The median household lived in a two storey semi-detached house in an urban/suburban environment. On average there were 5 heated habitable rooms in each property, which was on average constructed between 1950 and 1966. There were on average 2 people living in each property where roughly a third were retired, and third worked full time in a household with children. The median household (37%) described themselves as lower middle class while 71% described themselves as upper, middle, or lower middle class. Households on average owned 40 electrical appliances with a range between 13 and 85 appliances.

16 Proposed Dynamic Pricing

We shall first outline the theoretical foundation for the proposed TOU tariff. The tariffs do not, however vary with historical real time conditions in the electricity market. in subsection 16.1. Subsection 16.2 then proceeds to outline how the tariffs are constructed. Where we refer to TOU tariffs, in reality the tariff arrived at in this analysis is perhaps more closely akin to real time pricing. The tariffs do not, however vary with historical real time conditions in the electricity market. We shall examine 3 tariffs with increasing price dispersion, however all are revenue-neutral relative to a flat-rate tariff of 20 cents per kWh for the sample of households from the HES. The underlying shape of the tariff is based upon average GB demand by settlement period in order

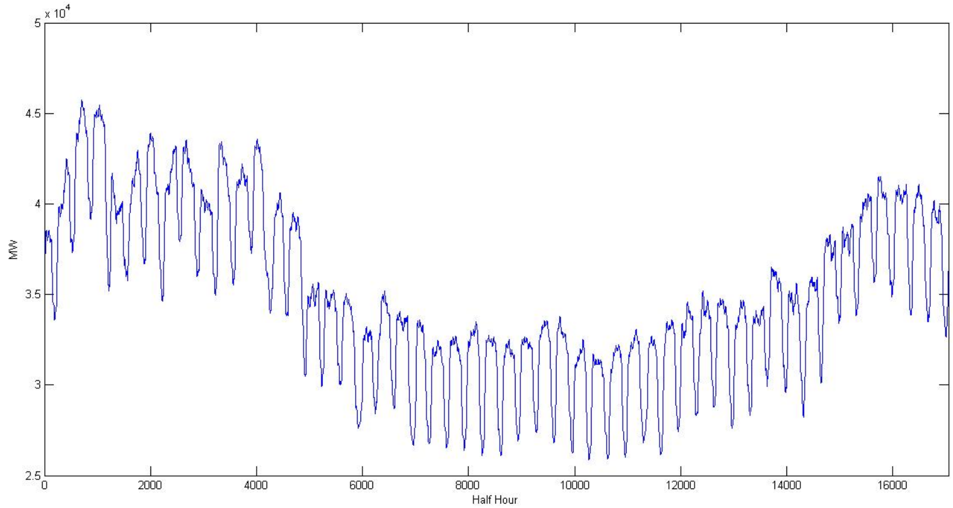
[44] For a histogram of household observation length see figure 39 in the appendix.

to approximate the real cost of supplying electricity to residential consumers. Generation is broadly scheduled in merit order meaning that lower marginal cost generation is scheduled first with higher marginal cost generation meeting peak demand. Furthermore, local shortages and so higher wholesale prices are more likely in times of peak demand. We therefore use the diurnal pattern of demand as the basis of our revenue-neutral tariffs. We price our tariffs at the settlement period/half hourly level in order to give us the highest possible degree of granulation. It would be interesting to examine the distributional effects of seasonal variations in residential electricity price, however we do not observe enough households in order to make any clear judgments on how seasonal tariffs would affect consumers. Furthermore, heating is mainly provided by gas in Great Britain, and given the limited need for space cooling in summer there is not as large a variation in generation between summer and winter as in other countries. Residential consumers could try to lower their consumption in peak times, such as in the evening in winter, however they can not generally shift their electricity consumption from winter to summer in the face of TOU tariffs, and so a seasonal tariff would lack that benefits of efficient TOU pricing. See figure 13 for a plot of daily average demand across 2014.

16.1 Theoretical Tariff Structure

The TOU tariffs under analysis here are identical in design to those studied in Borenstein (2013) and have the same underlying theory behind them. Although the precise structure of the proposed TOU and flat-rate tariffs does not affect the welfare analysis per se (we could for example arbitrarily impose the TOU tariff on all consumers), it is useful to construct a setting under which we can visualise these tariffs operating. The tariffs under analysis are designed to be revenue-

Figure 13: Daily Average GB Electricity Demand, 2014



neutral, whilst also reflecting the true cost of providing electricity[45]. Borenstein (2013) outlines four fundamental goals for his proposed residential tariff design, inspired by Bonbright et al. in *Principles of public utility regulation,* (1989). These are that the tariff should: cover the cost of providing power; provide efficient pricing; minimise bill volatility; and there should be no undue cross-subsidisation among consumers.

Firstly we assume there are two tariffs available to consumers: a flat rate tariff; and a TOU tariff where consumers are charged according to when they consume. Furthermore, the TOU tariff is optional - consumers are by default enrolled on the flat-rate tariff and can opt-in to TOU pricing. The tariffs are also designed to be equitable and revenue-neutral, meaning that each group of consumers (TOU and flat-rate) should cover the cost of providing power to each group (i.e. there should be no cross-subsidisation), and the combined revenues from the two tariffs should not exceed what would have been collected if TOU

[45]For a fuller discussion of equitable opt-in dynamic tariffs see Borenstein (2013).

tariffs were not available (assuming consumption behaviour is unchanged by the introduction of TOU tariffs).

We now postulate how the adoption of the TOU tariff may develop. As a starting point let us assume that the initial TOU tariff would be revenue neutral if the average consumer with an average consumption profile were to switch to the tariff. Consumers could then potentially be informed of their potential savings through the installation of smart meters and shadow billing. If we assume consumers are perfectly informed of their potential savings, and switching costs are not prohibitive then those consumers who demanded power disproportionately in low cost periods would switch to TOU pricing. Indeed all consumers up to the marginal consumer would switch.

Now the consumer profile of the two tariffs is very different. Those on the TOU tariff generally consume in low cost periods and so on average the cost of supply electricity to these consumers is lower than those who remain on the flat rate tariff. If the two tariffs are to remain equitable then the price of these two tariffs must change to reflect the changed demography. The flat-rate tariff therefore increases and the TOU decreases relative to the initial proposal. The marginal consumer is therefore no longer marginal and would switch to the TOU tariff. Consumers would keep on switching as the flat-rate tariff became more and more expensive. Indeed this would continue until all consumers, barring the most expensive consumer, who would be indifferent between switching and not switching, are on the TOU tariff. While this may at the outset seem unfair to the consumers who demand power when it is at it's most expensive (they are being charged more when they potentially need the power most) all that has happened is that the cross-subsidisation of consumers, which is the case under flat-rate tariffs, has been removed. The price faced by the end consumer is now reflecting marginal cost and consumers are provided with an efficient incentive for the timing of their consumption.

If consumers responded to these more efficient price signals by moving consumption from high cost to low cost periods then the process outlined above would only be exacerbated (and in turn beneficial to both generators and consumers alike). However, in reality, the unraveling process outlined above would probably not continue to its conclusion. As I demonstrate later (and was found for California in Borenstein [2013]), the changes in consumers bills are relatively small, and therefore would perhaps not induce all customers to switch to a TOU tariff. If consumers go on to lower or move their consumption to lower cost periods then the potential savings may be much higher.

However, Borenstein and Holland (2005) find that this kind of response tends to lower, rather than increase, the price for customers who remain on the default flat-rate. This is because if those on TOU tariffs redistribute their demand to lower their bills, then as the share consumers on TOU tariffs increases, the wholesale price at peak times drops. Of course the off-peak price will increase as demand is shifted off-peak, however, if peak time prices drop sufficiently relative to the increase in off-peak prices then those on flat-rate tariffs can become better off. Borenstein and Holland (2005) also show that those customers who are originally on TOU tariffs can become worse off as the share consumers on TOU tariffs increases.

There could however be social welfare reasons for retaining flat-rate tariffs. For example if flat-rates were progressive, or TOU tariffs were regressive in nature then the cross-subsidisation of consumers could be justified for social reasons. Indeed this is a potentially significant source of opposition to TOU tariffs. This analysis therefore seeks to explore these possibilities in section 17.

16.2 Tariff Construction

Each tariff is based upon the diurnal profile of average GB electricity demand, reflecting the true cost of generating and distributing electricity. In order to generate different spreads in residential electricity price for each tariff we take the basic diurnal shape of electricity demand and stretch out the series to create a different spread for each tariff. This allows us to have half hour prices which are up to ten times as much as the minimum price.

We first take the consumption data supplied by the HES and apply a flat-rate charge of 20 cents per kWh to it. This provides us with total and average spends for each household, and a total spend across the whole sample of households. The proposed tariffs will then be revenue-neutral against the total spend on a flat-rate tariff. We then take an average of 2014 GB electricity demand for each half hour/settlement period. This provides us with the diurnal profile of average GB demand to base our tariffs on. See figure 12 the average GB demand by settlement period.

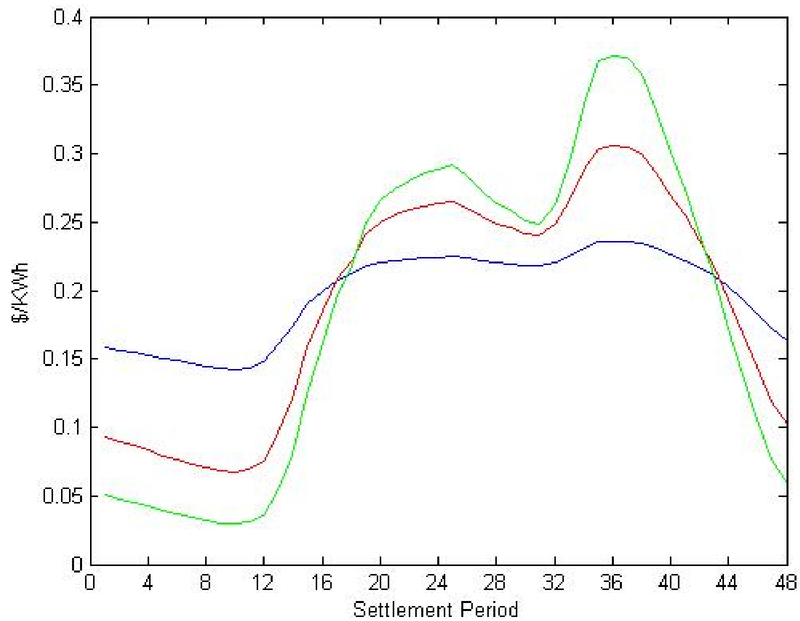
The settlement period averages are then transformed into proportions of the maximum value of average GB electricity demand. For example for the settlement period with the highest average GB demand the proportion would be 1. If the minimum was half of the maximum then that settlement period would take on the value 0.5. This provides the basis of the proposed tariffs. The half hour with the highest GB electricity demand will have the highest residential electricity price. The minimum demand period will have the lowest residential electricity price. If we used the proportion of maximum average demand then the in the example above the minimum price would be half that of the maximum. This proportion based profile would provide us with a fairly wide spread of prices already, however to increase the spread between electricity prices we take the cube, and the fifth power of these proportions to give us more variation in electricity price.

We then transform these daily proportion profiles into prices by calculating the scalar we can multiply the series by in order for the proposed price profile to be revenue-neutral. This involves first multiplying each tariff proportion by the total kWh consumed by the sample households in each settlement period. We then calculate the scalar the sum of these consumption weighted proportions can be multiplied by in order for the proposed tariff and the original flat-rate tariff of 20 cents per kWh to be revenue-neutral.

We can see in figure 14 the resulting tariffs based on GB demand. The flattest profile is based upon each settlement periods average GB demand as a proportion of the highest average settlement period GB demand. The more dispersed profiles with a greater spread in prices are based upon the cube, and fifth powers of the proportion as described above. We can see that for the fifth power tariff schedule (the tariff with the greatest spread) the lowest half hourly price is roughly a tenth of the highest half hourly price. The different tariff spreads then allow us to explore how sensitive our distributional welfare analysis is to how variable the tariff structure is.

It is important to note at this point that the HES does not record what electricity tariff each household was on. We therefore do not know what marginal price they were already facing, or indeed whether they were already reacting to tariff structures like economy 7. While this may bias our analysis there is reason to not be overly worried. Residential electricity prices are relatively homogeneous and consumers are not very price responsive since they face either a flat-rate or simple differential tariff.

Figure 14: Tariff by Settlement Period



17 Welfare Analysis

In this section we shall explore the distributional effects of the change from a flat-rate tariff to the TOU tariffs proposed in section 16.2. Concerns about the distribution of winners and losers have the potential to thwart the implementation of TOU tariffs if they are seen to be regressive, or risky by imposing large changes to individual households electricity bills. In order to examine these issues we have constructed three tariffs to based upon average electricity demand each settlement period so as to reflect the higher costs associated with meeting demand at peak times. Each tariff is revenue-neutral relative to a flat-rate of 20 cents per kWh, however we have accentuated tariffs 2 and 3 to give us greater spread in the marginal price throughout the day. The three tariffs are depicted in figure 14.

In subsection 17.1 we assume no demand in response to the proposed TOU tariffs. Consumption is assumed to be unchanged and therefore consumers have a price elasticity of demand of 0. In subsection 17.2 we allow households to adjust their consumption in response to the new TOU tariffs. In the demand response analysis we examine two different price elasticities of demand: -0.1, and -0.3 respectively, as studied in Borenstein (2013). As he notes, it would be unlikely for the elasticity of demand to be larger than -0.1 in absolute terms in the short run. However, as demand response technology improved, including potentially automating residential demand response, a price elasticity of -0.3 would become a better approximation.

17.1 Mandatory Time-of-Use Pricing without Demand Response

A good starting point for analysing how mandatory TOU tariffs would affect consumers is to look at the distribution of annual bill changes from the flat-rate tariff of 20 cents per kWh to the TOU tariffs proposed in figure 14. Figure 15 provides a summary of the change in the distribution of annual bills.[46] We can see that for the tariff with the least spread in price, TOU tariff 1, there is very little change to households bills. Most consumers see a very small fall whilst a small minority of households who use energy disproportionately at peak times see their bills increase up to 6%. TOU tariff 2 provides a much greater spread in prices throughout the day, and so we see much larger changes to consumer bills. The distribution is skewed to the right, having a fat right hand tail meaning

[46] Individual histograms can be found in the appendix in figures 40, 41, and 42 for TOU tariffs 1, 2, and 3 respectively.

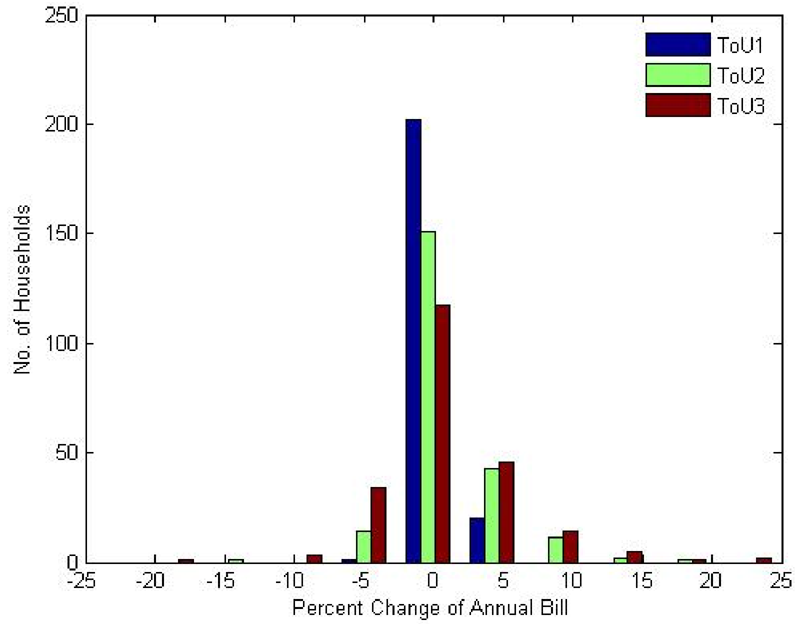
that many households see their bills unchanged or decreased slightly whereas a significant minority see their bills rise up to 17%. This is repeated for households facing TOU tariff 3 where we once again observe a positive skew. The right hand tail is more pronounced with some households seeing their bills increase up to 25%. The median consumer sees their annual bill fall whilst those who consume disproportionately at peak times see their bills increase. This is reassuring as, even without demand response and the associated decrease in energy costs, we predict more than 50% of consumers will see their bill fall.

However, even under TOU tariff 3, the range of bill change is reasonably small. Tariff has a significant spread of prices, indeed, the peak price is roughly 10 times the lowest price and yet we see bills changing by a relatively small amount. Only 3 of our 224 households would see their bills change by more than 20% in absolute terms. Indeed only 11 households would see their bills rise by 10% or more, and 35 see their bills increase by 5% or more. However, only 8 households saw their bill decrease by more than 5% with 105 households seeing their bills drop by under 5%. TOU tariff 3 would therefore on average redistribute from the few who used electricity disproportionately at times of peak demand to the many who do not.

These results are similar to those found by Borenstein (2013) who shows a positive skew to the change in household electricity bills in the face of mandatory TOU pricing. Borenstein (2013) also find similar proportions of consumers who would see their bills change by 20% or more. However, it is worth noting that TOU tariff 3 has a much greater spread in prices than those studied by Borenstein. This implies that electricity providers in Great Britain would able to give substantially stronger price signals for a given distributional change in annual electricity bills than California.

We have shown that even for tariffs with a large spread in residential electric-

Figure 15: Distributions of annual bill change from flat-rate to TOU tariffs



ity prices there is not a substantial effect on household annual bills. However, we may still be concerned about where the incidence of the bill changes falls. A tariff structure which was regressive or affects certain sections of society much more heavily than others would potentially cause enough concern to prevent adoption.

It would be interesting to explore the geographical spread of bill changes, as more northern areas of the country have fewer hours of daylight and so have more demand for electric lighting, however the HES does not provide any information on the location of households. The HES does provide information on household social grade, working status, electricity usage, the number of electrical appliances, the number of heated habitable rooms in the property, and the household type such as household with children, retired household, etc. We provide a breakdown of how these various groups would be effected by the proposed TOU tariff 3 in tables 7 and 8[47].

Table 7: Distribution of average bill change by usage, no. of appliances, and no. of rooms

Annual usage (kWh)	%	No. of Appliance	%	No. of Rooms	%
Q<1000	-1.76	Q≤20	0.93	1-2	-3.58
1000<Q<1600	0.57	21≤Q≤40	1.19	3-4	1.75
1600<Q<2200	1.89	41≤Q≤60	0.31	5-6	0.9
2200<Q<2800	1.65	Q≥61	1.15	7-8	1.09
Q>2800	1.44			9-10	-1.75

Table 8: Distribution of bill change by working status, social grade, and household type

Working Status	%	Social Grade	%	Household Type	%
Full time	0.2	A	2.74	Single non pensioner	-0.62
Part time	1.54	B	-0.43	Multiple person	1.81
In education	1.57	C1	0.6	Household with children	0.69
Unemployed	0.13	C2	1.19	Pensioner	0.84
Retired	1.34	D	3.26		
		E	3.59		

Table 7 displays the average percentage change in households annual electricity bill by annual usage, the number of electrical appliances a household owns, and the number of heated habitable rooms in the property. One way to look at these three indicators is to think of them as being proxies for a household's wealth, or income. Reassuringly we find that higher levels of usage are associated with an increase in the average annual bill. Households with higher electricity use would face an increase in their bills relative to low use households, and so be contributing more to the upkeep of the system they use more[48]. However, there is little pattern to how households bills would change by the number

[47]We provide this analysis only for TOU tariff 3 because TOU tariffs 1 and 2 are transformations of tariff 3 and so should convey the same information, except with lower values, given the reduced spread in prices.

[48] The distribution of annual usage can be found in figure 43 in the appendix.

of appliances or rooms in the property. There is a lot of heterogeneity within appliance and room number groups and it appears likely that neither are strongly related to annual bill change. However, the relatively small sample size makes it hard to say for certain.

Table 8 displays the average percentage change in households annual electricity bill by working status, social grade, and household type respectively. There does not appear to be any discernible trend with respect to working status or household type. The effects within each group were again very heterogeneous and were not strongly related to working status or household type. TOU tariff 3 does appear to be regressive with respect to it's effect on households in social grades D and E. However, the standard errors were large, and the effect on households was very heterogeneous within each group.

Annual bill change appears to be uncorrelated with the variables used, however the sample size was relatively small and the standard errors were large. Generally there was a lot of heterogeneity in annual bill change, even within each category under analysis and as such these gave little inclination as to who may be affected by the introduction of TOU tariffs. This is reassuring in one respect since it appears a change to TOU tariff 3 would be neither regressive nor progressive and simply reward those who consumed less, and at times of spare capacity. However, the small sample size makes it hard to say with any surety. Higher levels of annual usage appear to indicate a higher electricity bill, relative to low users, under TOU pricing, which again is reassuring. Annual usage was also positively correlated with bill change, with a correlation coefficient of 0.21.

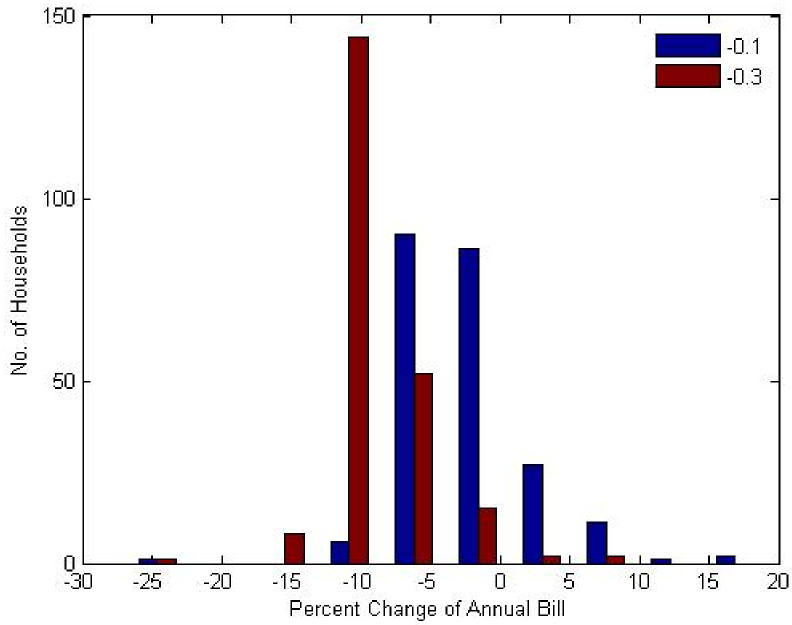
17.2 Mandatory Time-of-Use Pricing with Demand Response

The analysis up until this point has assumed that consumers will not change their consumption patterns in the face of a switch a TOU tariff, that their price elasticity of demand is 0. However, with the advent of smart meters it is entirely feasible that consumers would know exactly what price they face at each point in time, and even be able to automate some of their consumption to take advantage of the tariff profile. For example through electric heating, electric cars, and the operation of large white goods. In this subsection we therefore incorporate demand response to the analysis given in subsection 17.1.

When we constructed the TOU tariffs we did so under the assumption that a move from flat-rate to TOU tariff would be revenue-neutral. Here we allow household consumption to change and so if we are to keep the tariffs revenue-neutral we must make more stringent assumptions about the generation cost structure. We must assume that changes in quantity under the TOU tariff impose marginal costs that are equal to the TOU tariff rate. This would mean that the change in quantity did not require a tariff change in order to keep profit levels the same. Alternatively we could assume that the cost savings from running plant more efficiently (lowering peak production and increasing off-peak) are equal to the lower revenues collected.

Two price elasticities of demand shall be examined, as in Borenstein (2013). A short run elasticity of -0.1, and long run elasticity of -0.3, which is perhaps more reasonable as demand response technologies improve. We explore issues of demand response for TOU tariff 3 only for brevity since it provides us with the greatest price signals, and represents the greatest spread of prices likely in GB residential electricity pricing. Furthermore, tariffs 1 and 2 have the same shape as tariff 3 and so would provide us with similar results.

Figure 16: Distribution of annual bill change from flat-rate to tariff 3 with demand response

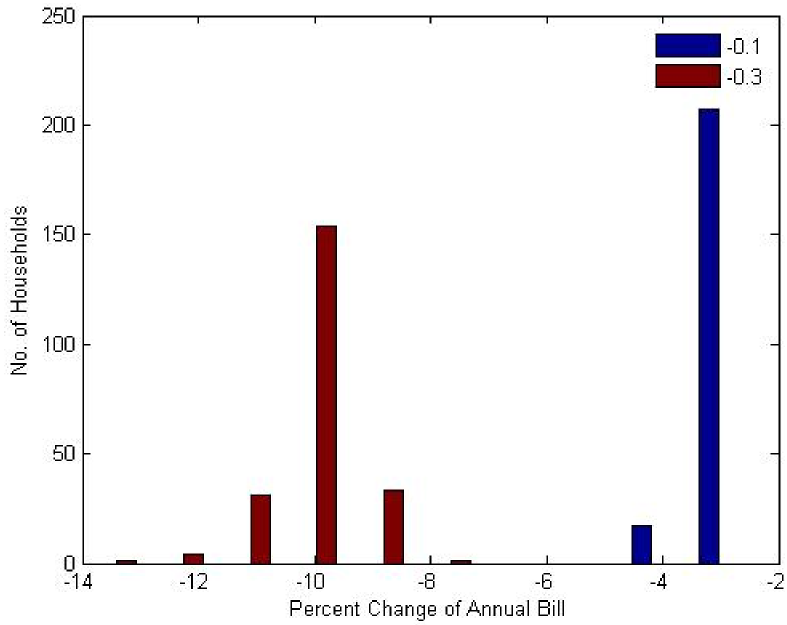


In order to explore the effects of demand response we construct alternative household consumption profiles in response to TOU tariff 3 assuming a constant elasticity demand function with price elasticities of -0.1, and -0.3 respectively. Figures 16 and 17 display the distribution of annual bill change from the flat-rate tariff, and tariff 3 with no demand response to tariff 3 with demand for each elasticity[49].

Figure 16 shows how households would be affected by the introduction of TOU tariff 3 compared to the flat-rate tariff, under an assumption of demand response. It is directly comparable to figure 42 in the appendix which shows the distribution of bill changes from a flat-rate tariff to TOU tariff 3 under an

[49] For a distribution of each bill change separately by elasticity see figures 45 through 48.

Figure 17: Distribution of annual bill change from tariff 3 with PED = 0 to tariff 3 with demand response



assumption of no demand response. Figure 17 shows the distribution of annual bill change from tariff 3 with no demand response to tariff 3 with demand response - alternatively, how households would be be affected from moving from an assumption of no demand response to demand response under tariff 3. We can see, unsurprisingly that under a modest price elasticity of -0.1 consumers are better off than under no demand response. The average bill is reduced 3.28% relative to the revenue-neutral level and only 46 of 224 households would see their bills rise relative to the flat-rate tariff with a maximum increase of 19% compared to 25% under no demand response.

Under a constant price elasticity of demand of -0.3 we see households become much better off than under the constant flat-rate tariff. Households would on average face nearly 10% lower electricity bills. Indeed only 5 households would see bill rise after a move to TOU tariff 3, with a maximum increase of 7.5%, and a maximum decrease of 27%. However, these kind of savings would only become possible when demand response technology was sophisticated enough for consumers could react sufficiently to prices. While the exact value of the price elasticity may be debatable it is important to note that these savings are only possible with the introduction of TOU tariffs. With flat-rate tariffs consumers face little incentive to move their consumption from times of high demand to low. With TOU tariffs and demand response technology consumers have the incentive and the means to do so. While we estimate how much this may lower households electricity bills it would also be beneficial for generators, distributors, and retailers as the costs of supplying electricity would be lower.

As mentioned earlier, we are implicitly assuming that for the TOU tariffs with demand response to be profit neutral either changes in quantity impose marginal costs equal to the TOU tariff rate at the time, or that the cost savings from running plant more efficiently are equivalent to the lower revenues collected. Under a price elasticity of demand of -0.1 we saw that households would save on average 3.28% of their current bill and under a demand elasticity of -0.3 they would save nearly 10% on average. While it is beyond the remit of this paper to estimate likely technical savings from more efficient consumption profiles it is perhaps unlikely that cost savings would be as much as 10%, especially when, under constant elasticity demand response, quantities demanded are the same before and after TOU tariff introduction. In fact it is feasible that consumers could increase their consumption in response to a TOU tariff as there could be an efficiency loss as a result of moving consumption to other parts of the day, for example heating.

Another way to think about the bill savings households would expect under TOU tariffs with demand response is how much electricity prices could increase and for households to remain on average better off. Electricity provision is highly capital intensive and generators tend to recover a disproportionate amount of their costs through high prices at times of peak demand. As consumers moved consumption away from peak periods, generators would likely see their profits fall, as has been seen in California with the introduction of distributed photovoltaic generation[50]. Indeed capacity market auctions have tried to address this to an extent in Great Britain.

Given that costs are unlikely to fall as much as 10% after the introduction of TOU tariffs it is therefore relatively likely retailers would seek to raise electricity prices in response to a fall in demand at peak times. However, given the system would be less costly to operate under more efficient pricing it is reasonable to assume the average consumer would see their bills stay the same if not decrease. Importantly, consumers who disproportionately consume at peak times would no longer be subsidised by those who do not as is the case under flat-rate tariffs.

18 Conclusion

In this chapter we have explored demand side management and TOU tariffs in particular. A clear threat to the adoption of TOU tariffs is the fear that there will be winners and losers and that this may run along socioeconomic lines. Indeed that they may be regressive or provoke an increase in residential electricity tariffs. We have therefore sought to analyse who would be affected by a switch to TOU tariffs and by how much using a novel data-set, the Household Electricity Survey (2013).

We construct revenue-neutral tariffs based upon the diurnal GB electricity

[50] This has been with increasing block pricing rather than TOU pricing however the principle remains the same. See Cohen, Kauzmann, and Callaway (2015), and Borenstein (2015) for further details.

demand profile to reflect the true cost of supplying electricity. We found that under revenue-neutral tariff setting with no demand response households are not exposed to excessive bill increases. The tariff with the greatest spread, TOU tariff 3, would see only 11 of the 224 households studied have their bills rise by more than 10% with a maximum increase of roughly 25%. A similar previous study, Borenstein (2013), found similar likely distributional effects despite this study having a much larger spread of prices than the previous study. A further analysis of household characteristics found household bill change to be uncorrelated with a range of socioeconomic indicators implying the tariffs proposed are not regressive in nature. However, the low sample size makes it hard to say for certain. We did find that bill increases were positively related to electricity use (although bill change was fairly heterogeneous within each demand range).

We then sought to analyse how consumers may be affected if they were able to respond to the changed pricing profile. Using constant elasticity demand functions with price elasticity of demands of -0.1, and -0.3 to represent the short term and long term response to TOU pricing we found that consumers could become much better off. Indeed under a constant elasticity of -0.3 households could expect 10% lower electricity bills on average. However, it is likely that retailers would seek to increase TOU prices in response in order to cover fixed costs of generation and for profits to be retained. The net effect would likely be beneficial for consumers, however, since the more efficient pricing of residential electricity would lead to more efficient consumption, generation and distribution, and generation and distribution costs would likely fall.

Importantly, under TOU tariffs consumers who use power disproportionately at times of low demand, and so low cost, would no longer be effectively subsidising those who use power disproportionately at time of peak demand, and so high cost, as they are currently under flat-rate tariffs. Furthermore, as more inflexible generation is added to the grid it may become desirable and possibly necessary for consumers to react to TOU prices in order to reduce the cost of meeting demand, and reduce the need for spare generation capacity. It is therefore reassuring to have evidence suggesting that even TOU tariffs with a very large spreads would produce relatively little dispersion in households electricity bills and are unlikely to be regressive.

We have used average demand by settlement period as a proxy for the true cost of supplying electricity, however with a much larger sample size it would be interesting to not only explore the effects of seasonal variations in electricity price, but also real-time pricing. Hogan (2014) points out that if TOU prices are set in advance then even very good TOU tariffs would miss the majority of efficiency gains that would result with the use of actual real-time prices. Figure 11, found in the introduction, provides some indication of this by showing that sell prices have a great deal of volatility to them, especially around times of peak demand. It would therefore be interesting to explore how bill change volatility was affected by a move to real-time pricing. However, the fact that we find electricity bill changes to be relatively small for even very large variations in price indicates that households should not be particularly adversely affected from a move to real-time pricing rather than preset TOU tariffs.

Key stakeholders who may be interested in the research documented in Chapter 3 are energy firms and policymakers exploring the potential for demand side response, including the system operator, DECC, and Ofgem. Furthermore, consumers fearing a loss of welfare on the introduction of demand side response may be interested in the results. We show that consumers will not be particularly adversely affected, and the only group who are potentially worse off are the consumers with high electricity usage. This is encouraging for consumers in general. However, given the relatively small effects we see on consumers bills, there is reason to believe consumers may not respond to these small potential gains and losses, and the cost of either monitoring software, or indeed the mental cost of monitoring and reacting to this price information may be too prohibitive. Indeed, the evidence from consumer switching behaviour in the energy market suggests consumers may need much bigger price signals in order to be motivated to alter their behaviour [51]. Therefore policymakers and energy firms considering introducing TOU or real time pricing may be interested in the results in order to gauge potential take up and activity within a demand side management scheme.

[51] See Giulietti et al [2014] for more detail on the evidence on consumer switching behaviour in the British electricity market.

Part IV

References and Appendix

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Appendix

Table 9: Summary Statistics

Variable	Mean	Standard Deviation
Gross Demand (MW)	56717	12459
Net Demand (MW)	51858	12830
Renewable Output (MW)	4859	4267
Price £/MWh (2)	210	56.5
Price £/MWh (4)	95	27
Price £/MWh (5)	80.5	20
Price £/MWh (6)	73	15.5
Price £/MWh (7)	69	12.5
Price £/MWh (8)	66.5	10.5
Price £/MWh (10)	64	9
Price £/MWh (12)	63	8

Output rounded to 1 s.f.

Price rounded to nearest 50p. Number in parenthesis denotes the number of firms in the market.

Figure 18: Gross Demand 2050

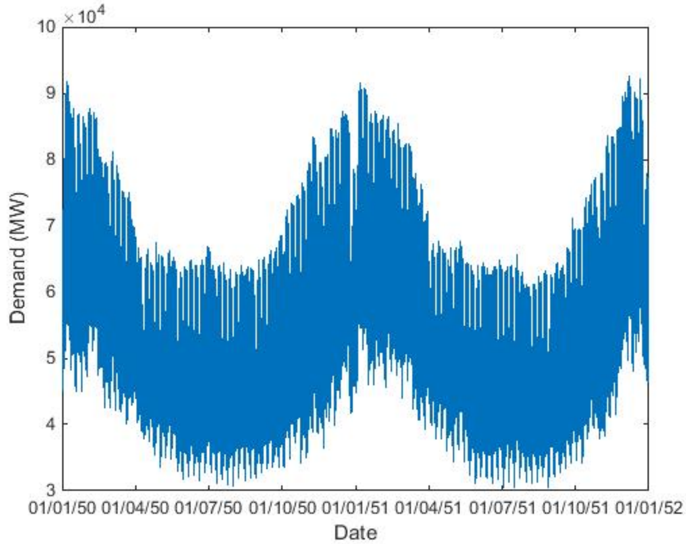

Figure 19: Net Demand 2050

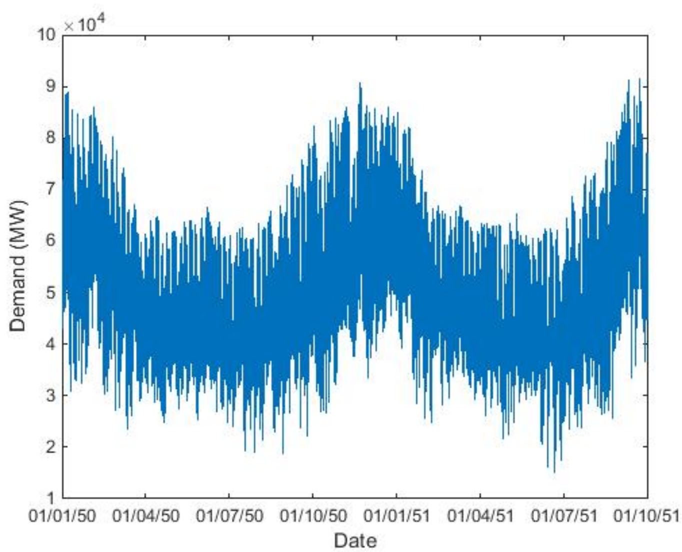

Figure 20: Renewable Output 2050

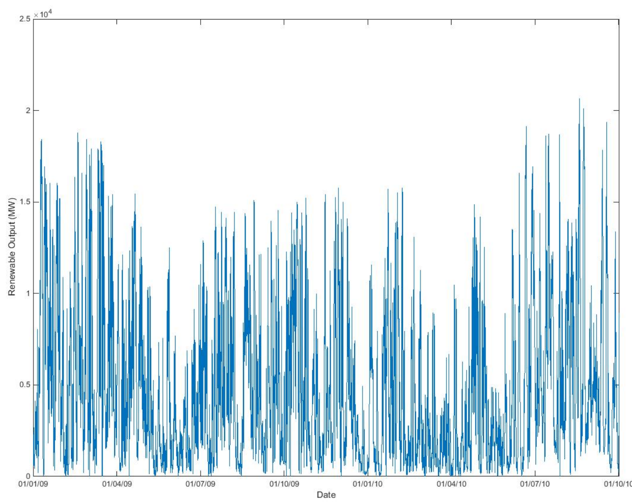

Figure 21: Histogram of Gross Demand 2050

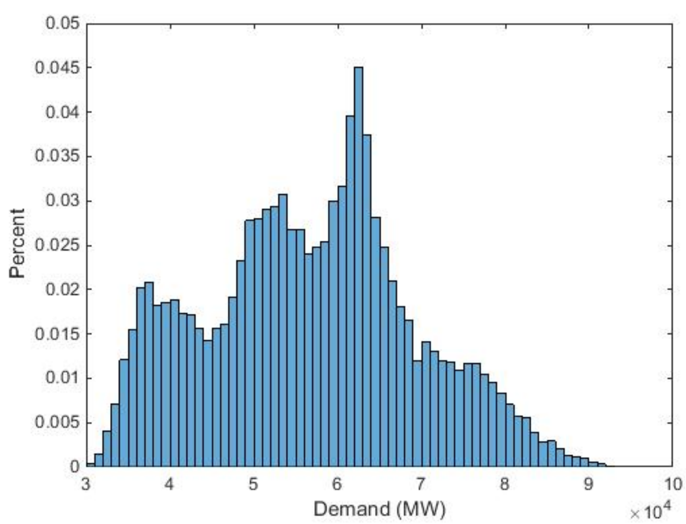

Figure 22: Histogram of Net Demand 2050

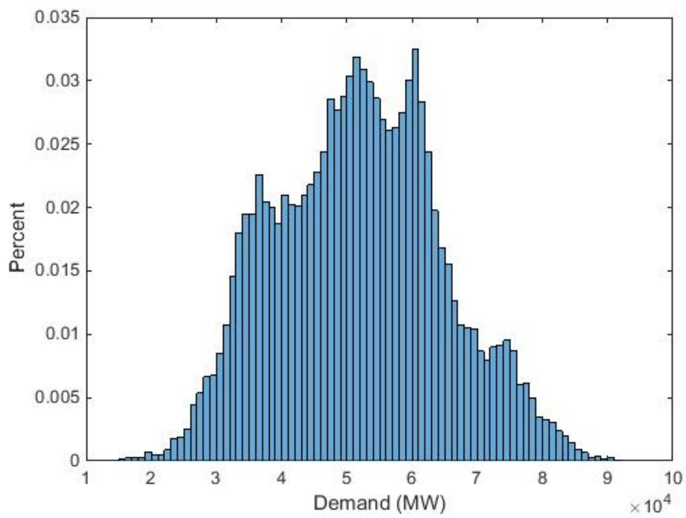

Figure 23: Histogram of Renewable Output 2050

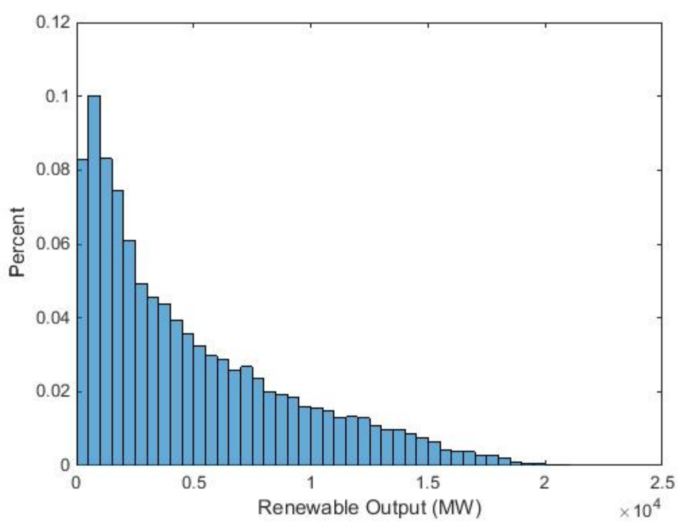

Figure 24: Diurnal Demand Profile

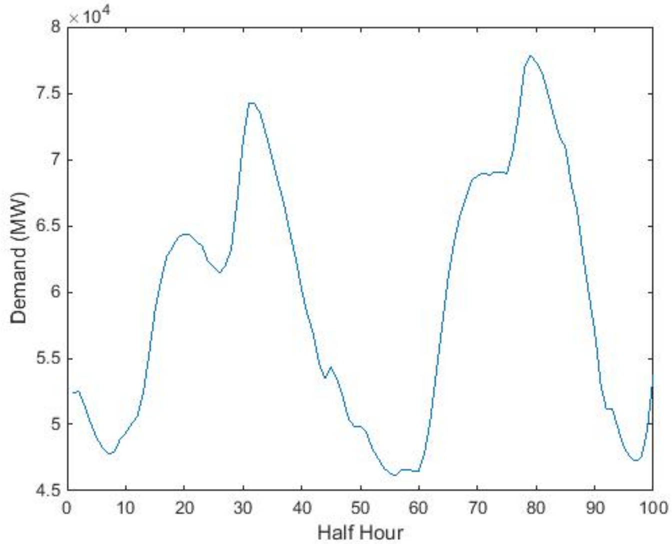

Figure 25: Intra-Week Demand Profile

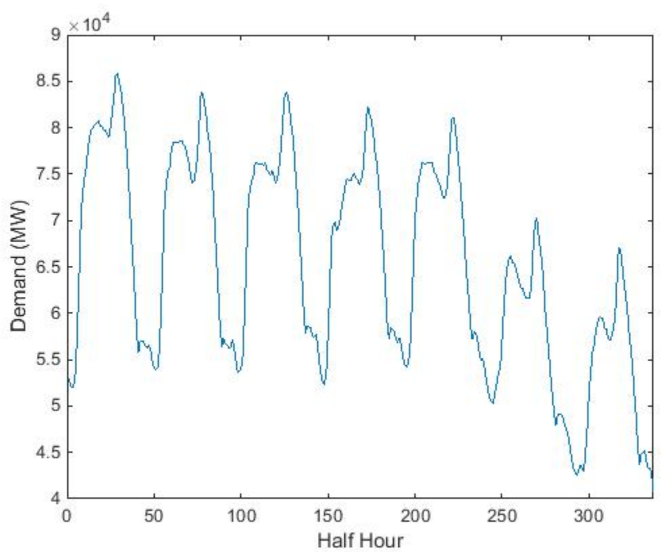

Figure 26: Prices for 6 Firms

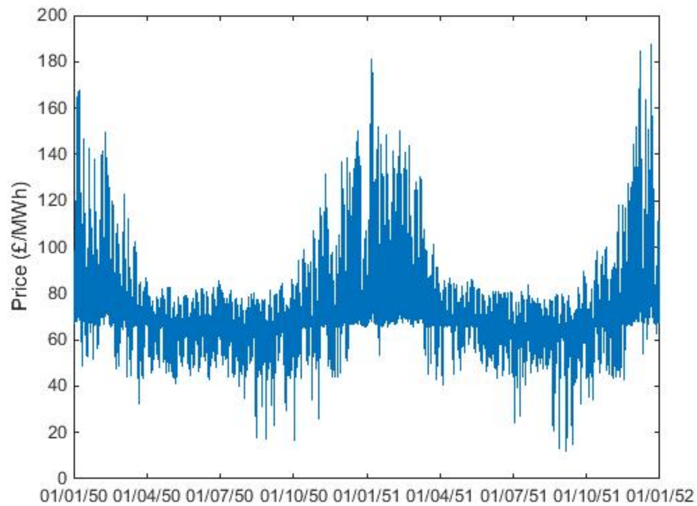

Figure 27: Histogram of Prices for 6 Firms

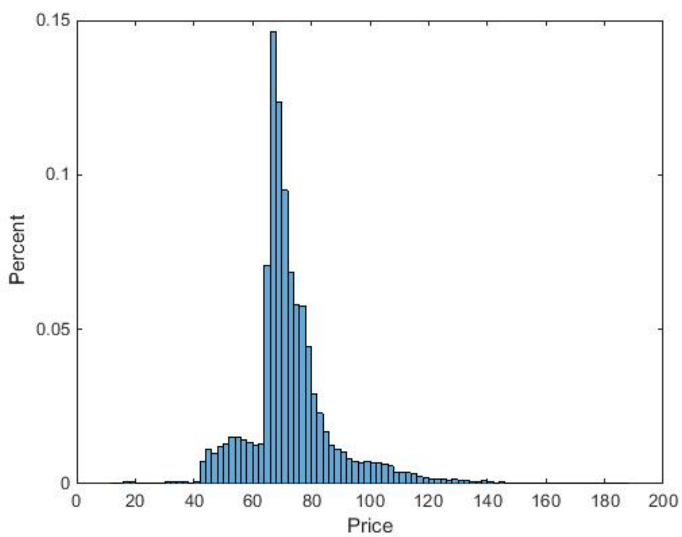

Figure 28: Arbitrage Returns, 20MWh Capacity

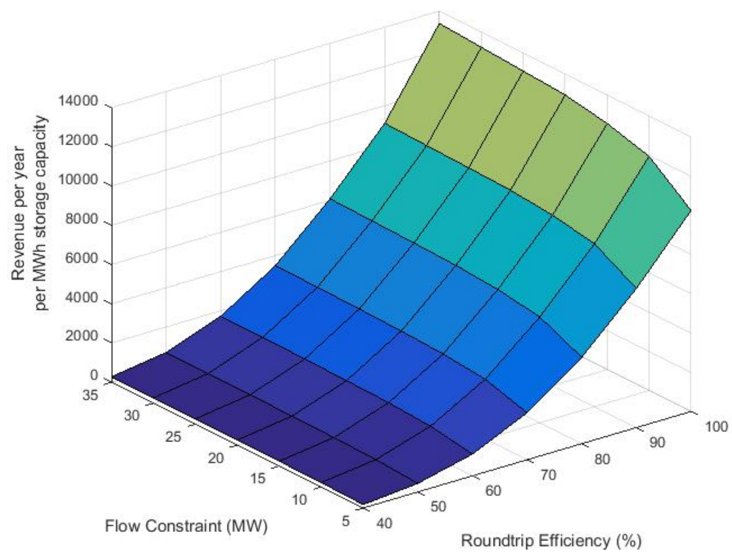

Figure 29: Arbitrage Returns, 40MWh Capacity

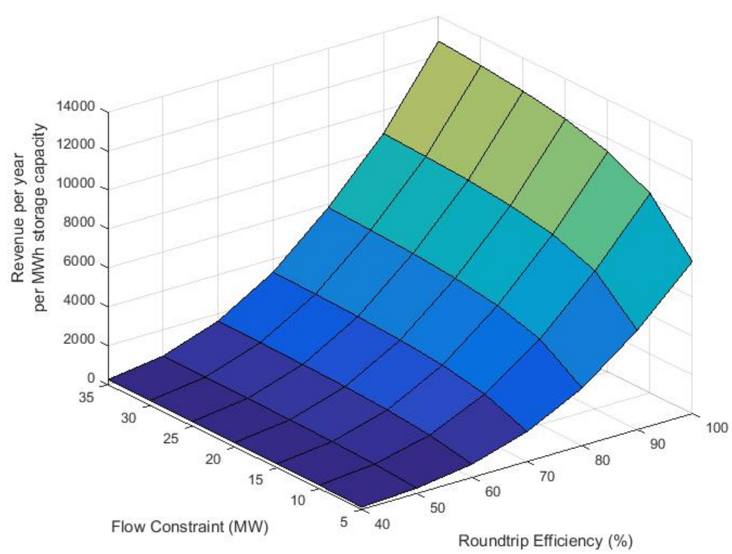

Figure 30: Arbitrage Returns, 60MWh Capacity

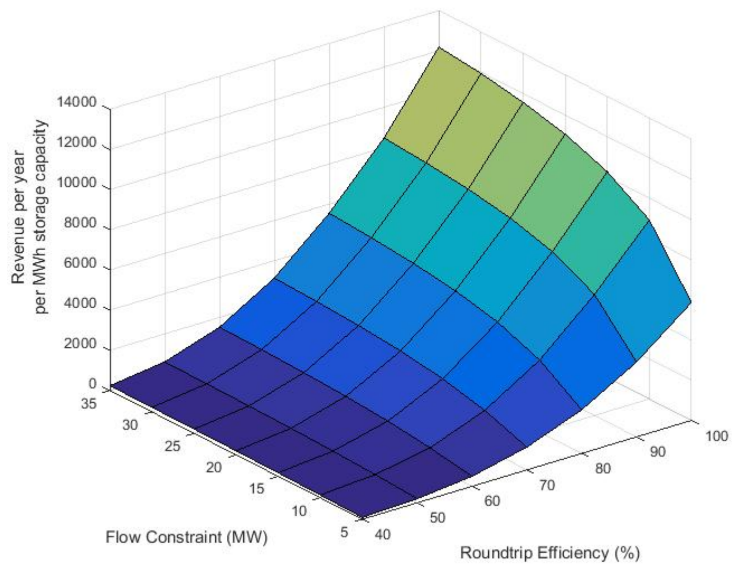

Figure 31: Arbitrage Returns, 80MWh Capacity

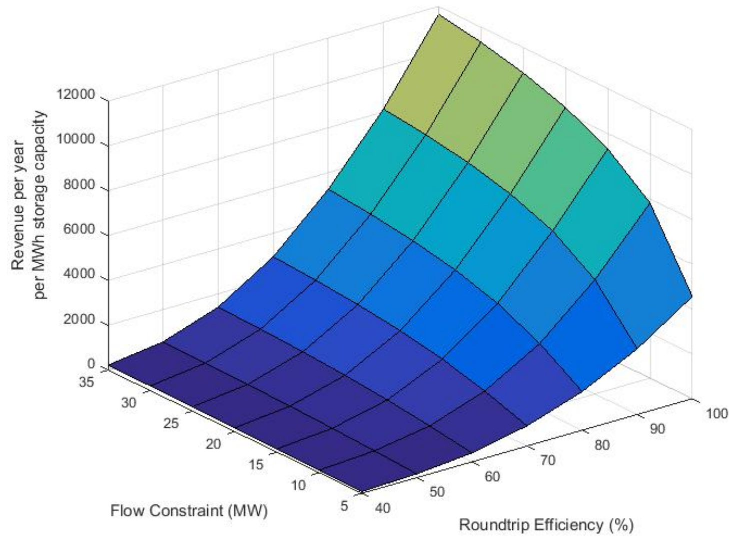

Figure 32: Arbitrage Returns, 100MWh Capacity

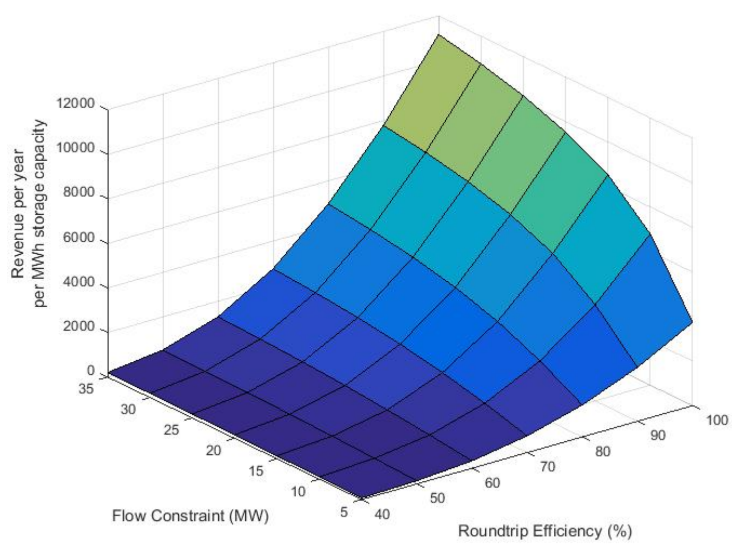

Figure 33: Operational Time, 20MWh Capacity

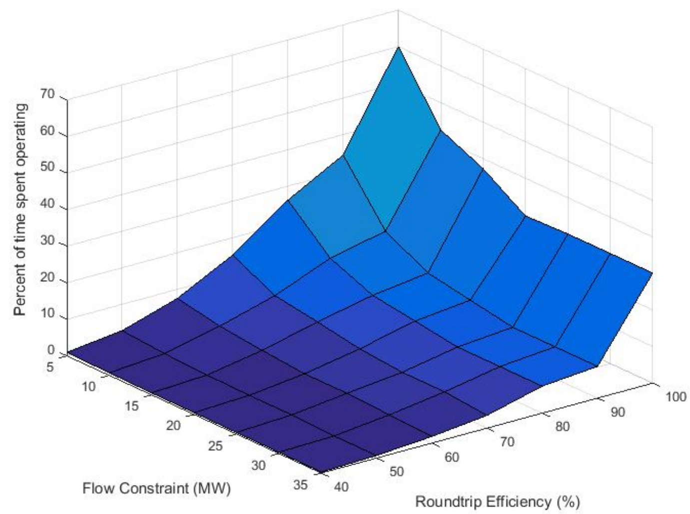

Figure 34: Operational Time, 40MWh Capacity

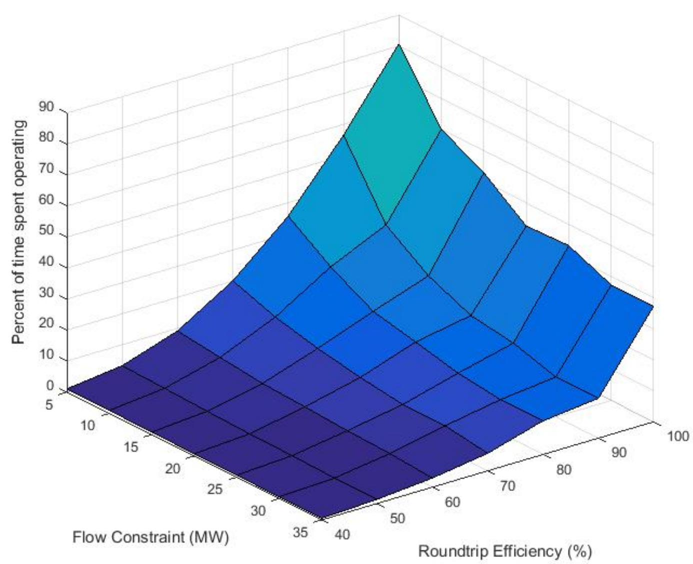

Figure 35: Operational Time, 60MWh Capacity

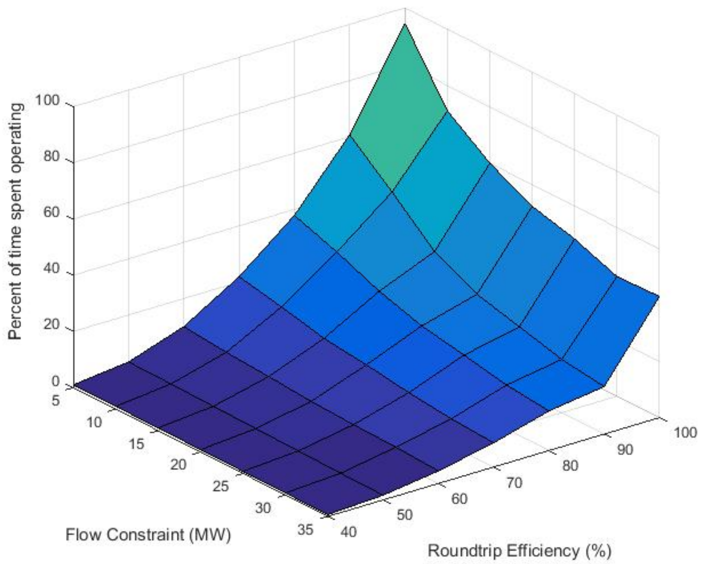

Figure 36: Operational Time, 80MWh Capacity

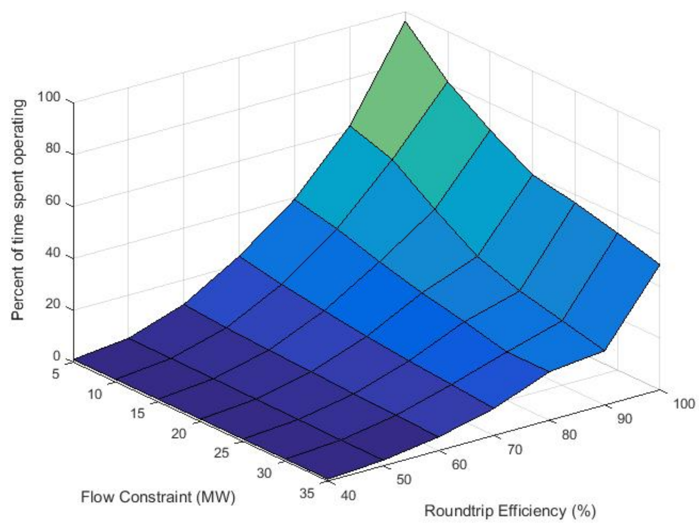

Figure 37: Operational Time, 100MWh Capacity

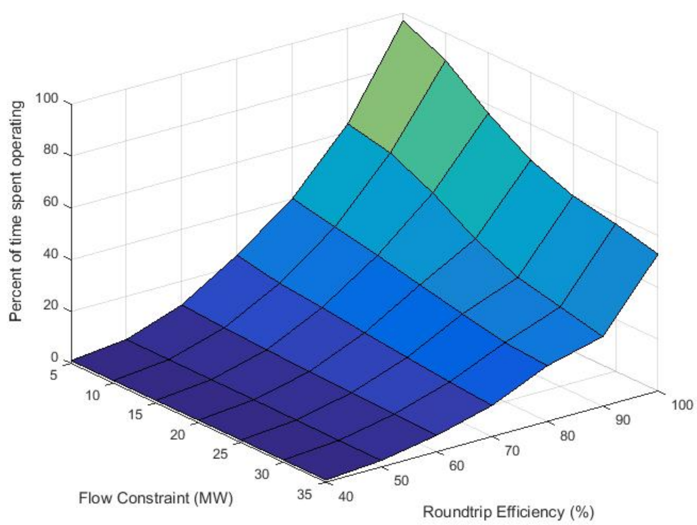

Figure 38: Equilibrium Computation

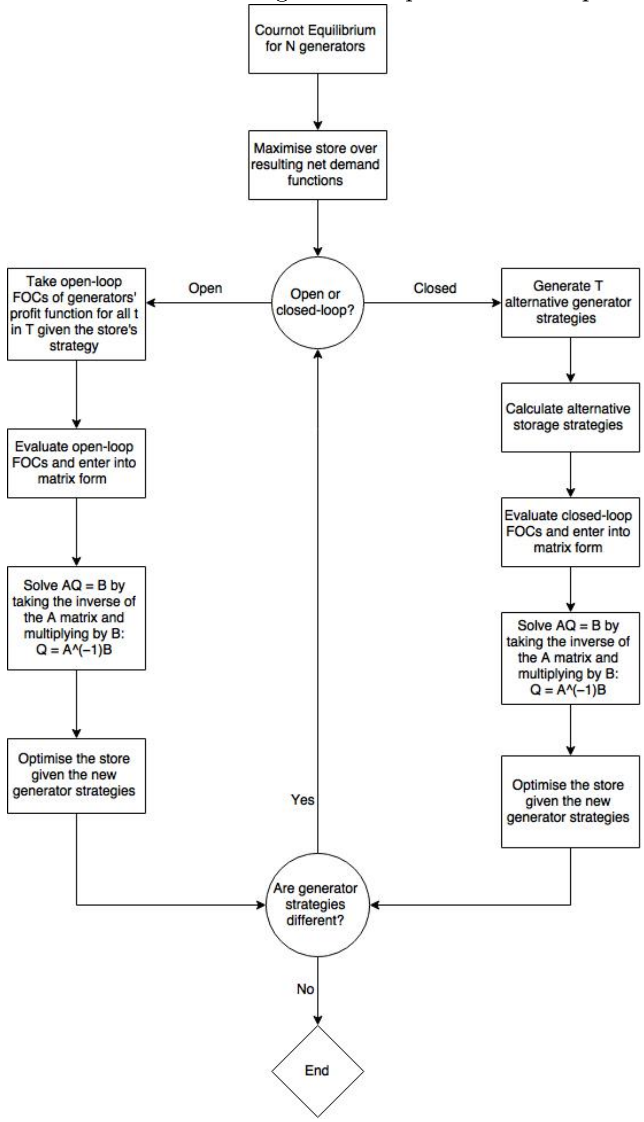

Figure 39: Household Observation Histogram

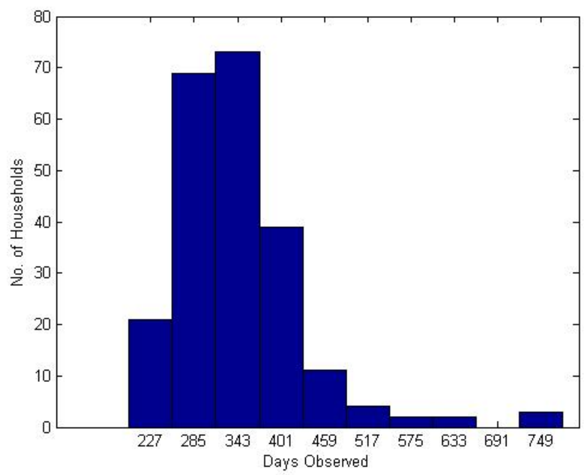

Figure 40: Distribution of annual bill change for tariff 1

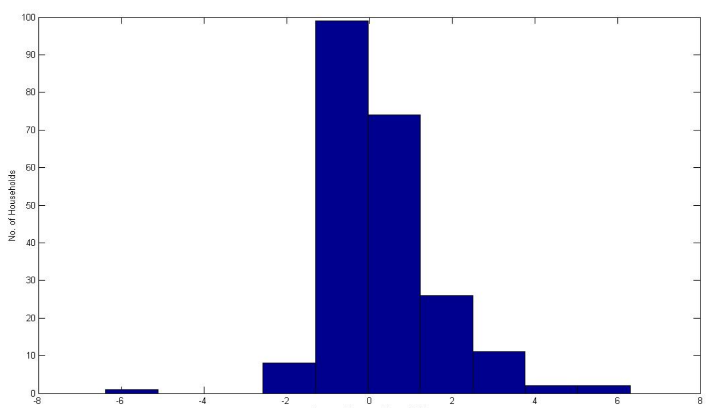

Figure 41: Distribution of annual bill change for tariff 2

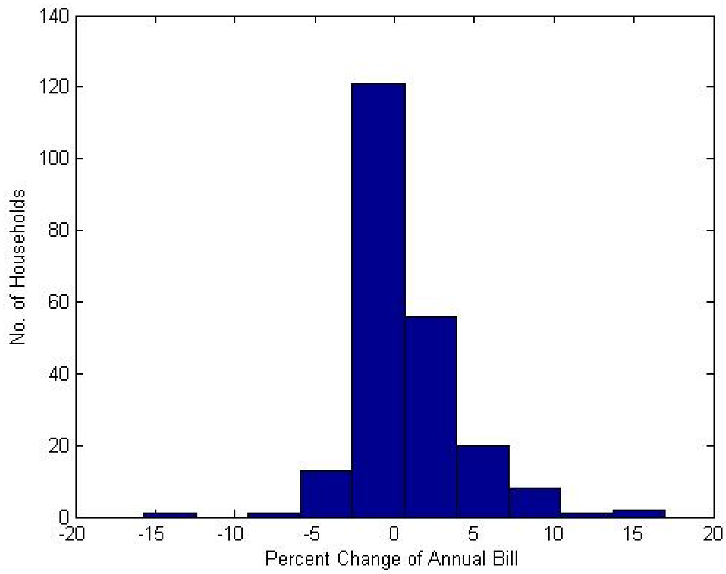

Figure 42: Distribution of annual bill change for tariff 3

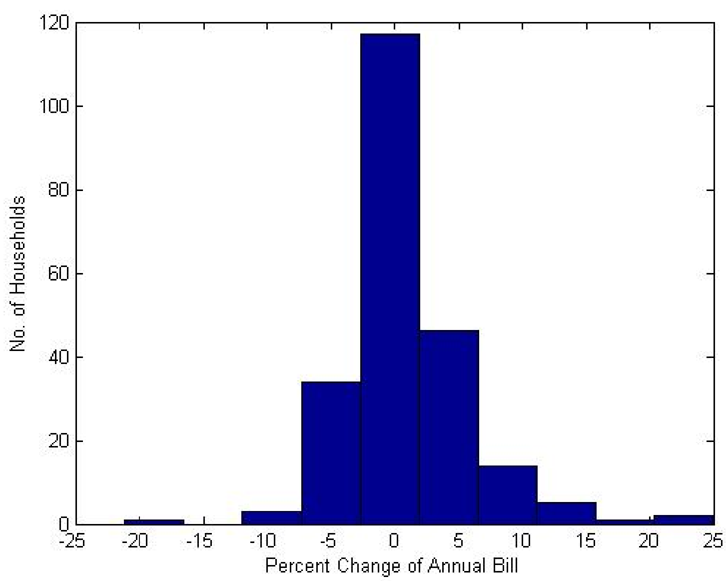

Figure 43: Distribution of household electricity usage

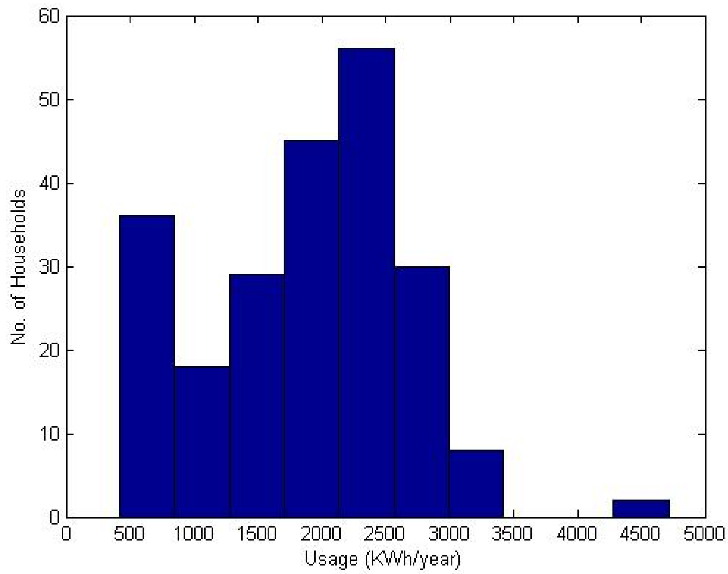

Figure 44: Distribution of electrical appliances

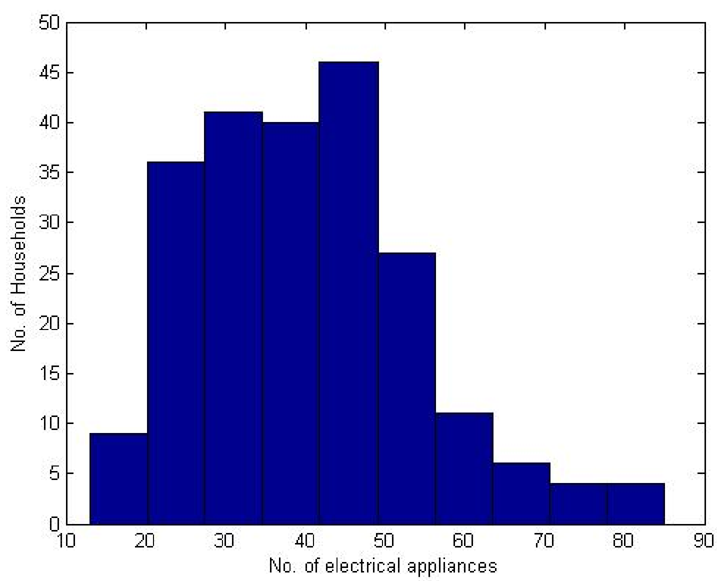

Figure 45: Distribution of annual bill change from flat-rate tariff to tariff 3 with PED = -0.1

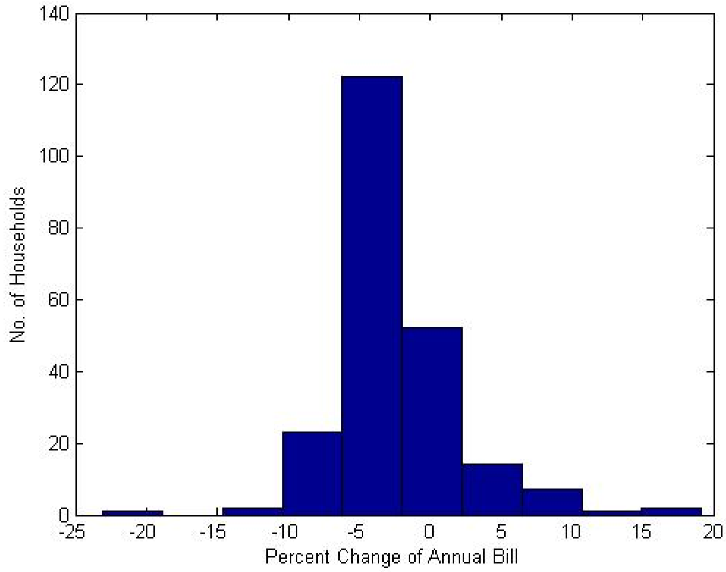

Figure 46: Distribution of annual bill change from flat-rate tariff to tariff 3 with PED = -0.3

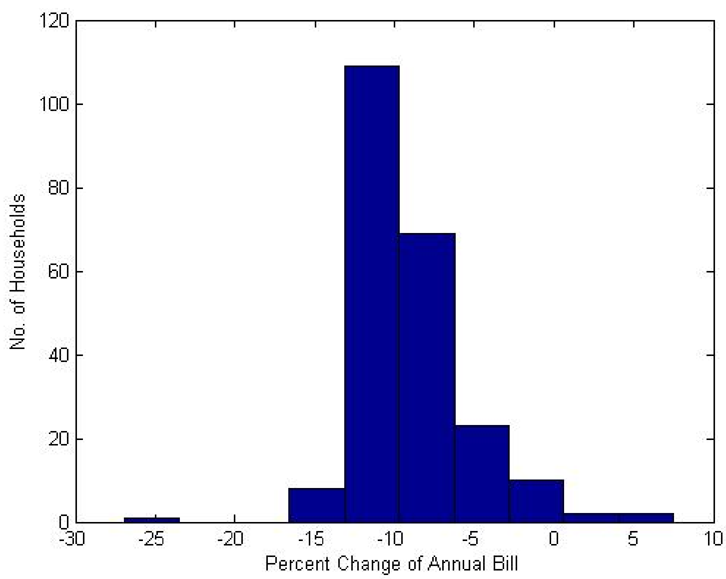

Figure 47: Distribution of annual bill change from tariff 3 with PED = 0 to tariff 3 with PED = -0.1

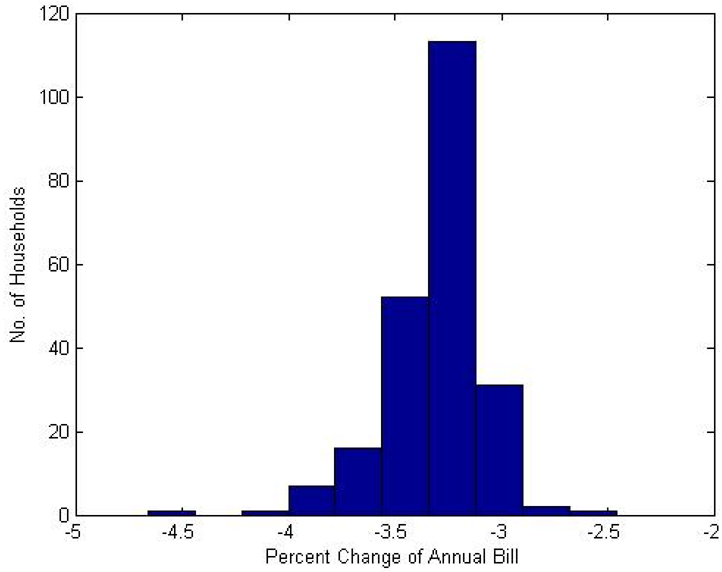

Figure 48: Distribution of annual bill change from tariff 3 with PED = 0 to tariff 3 with PED = -0.1